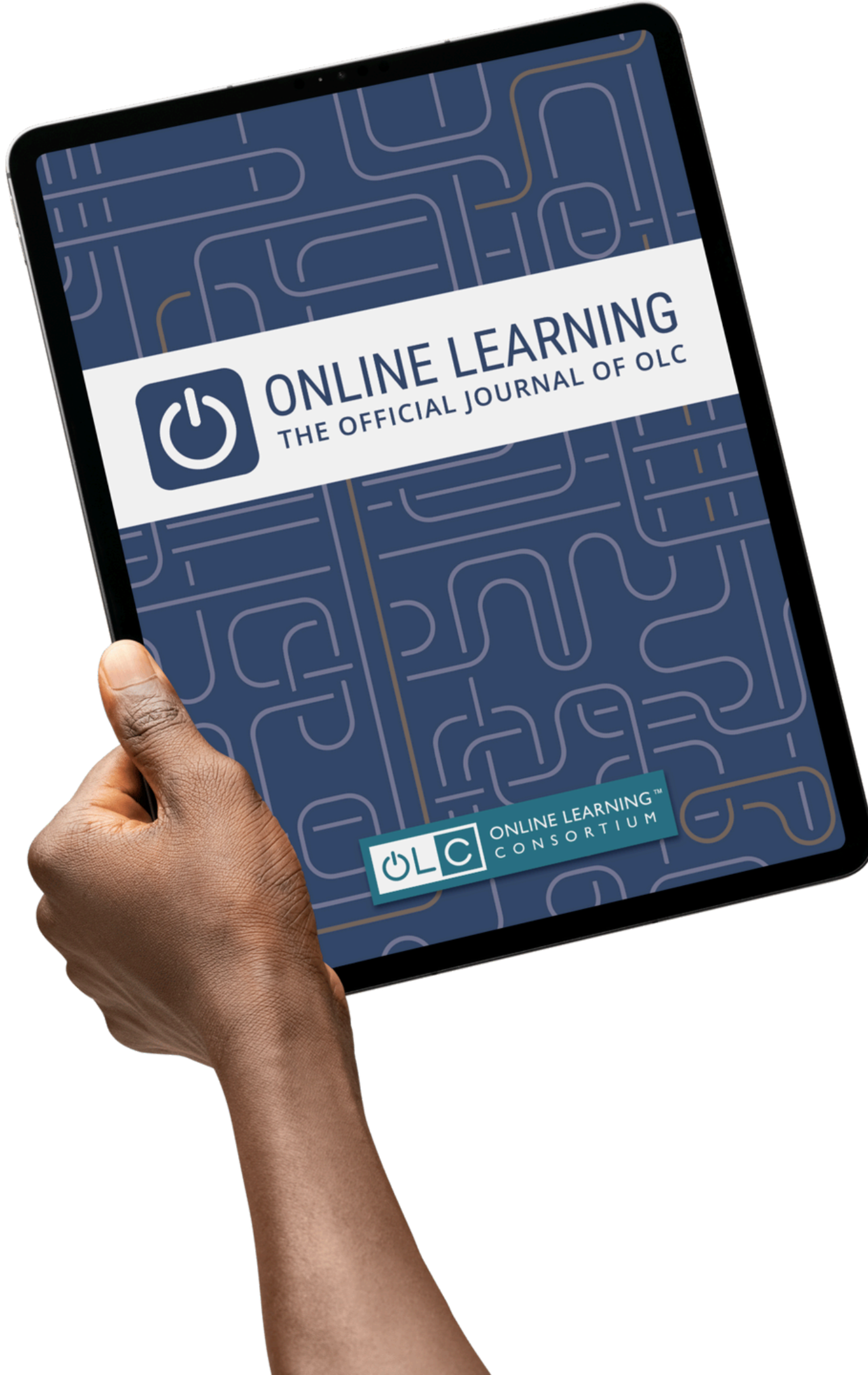




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Higher Education in an AI-Transformed World

Introduction to the Special Issue: Higher Education in an AI-Transformed World	v-ix
Artificial Intelligence and Digital Learning: Architecture, Hallucinations, Information, Findability, The First Rung, and The Arts of Inquiry	1-30
Understanding the Generative AI Divide: Faculty and Student Perspectives in Higher Education	31-48
Graduate Teacher Education Students Evaluate Generative AI: A Two-Year Comparison	49-62
Asked & Answered: Using AI to Nudge Student Metacognition and Responsibility for Learning	63-81
The Promise and Paradox of AI in Doctoral Education	82-105
Curriculum Mapping as a Tool for Continuous Improvement of the Business Studies (BS) Curriculum in a Digital-First University	106-129
Predicting Online Instructional Design Students' Intention to Use AI Tools: Value, Utility, and Self-Efficacy	130-152
Graduate Students at the Frontier of GenAI: Emerging Trends from a Southwest Borderland University	153-179
Transforming Enrollment Management in the Field of Online Learning	180-189
Educating the Educators About AI: Strategic Initiatives in a Graduate School of Education	190-217

Section II

Introduction to Section II	xi-xiii
Developing A Video-Based Discussion Platform with Emotion Detection Deep Learning to Increase Online Learning Engagement	218-245
Listening to Adjunct Faculty Voices: A Case Study for Supporting Adjunct Faculty Across Career Stages at a Small Community College	246-270
HyFlex Graduate Education: A Systematic Review	271-301
“I Get It Now”: Insights from Implementing Metacognitive Strategy Instruction through an Asynchronous Gradual Release of Responsibility Framework	302-330
Instructors’ Perceptions of Assessment Types and Strategies Used in Online Courses in Higher Education	331-353
Quantitative Investigation into Professional Development, Awareness of Neuromyths, General Knowledge about the Brain and Learning, and Evidence Based Practices in Higher Education	354-396
Questionnaire for Self-Regulated Learning in Blended Environments	397-433
Cognitive Demands and Course Pedagogical Design: Understanding Success in Online Learning Environments	434-458
The Efficacy of an Online Learning and Assessment Tool for COVID-19 Recovery Intervention	459-490
Effect of online and face-to-face engagement and formative assessment score in flipped programming course outcomes and satisfaction.	491-518
The Mediating Effect of Academic Buoyancy on the Causal Chains of Online Learning Readiness, Academic Motivation, and Academic Performance	519-534
Exploring Psychological Factors Affecting the Success of Online Learning in Higher Education in Indonesia	535-559
MOOC Videos in the Age of Streaming: Learners’ Preferences and Perceptions	560-580
Empowering the Next Generation: A Holistic Self-Care Course for Cultivating Resilience in Undergraduate Students	581-602

Caring School Leadership and Enabling School Structure	603-621
Enhancing Online Learning Readiness: How Student Engagement and Instructor Role Shape Success in Higher Education	622-645
Italian in-training teachers: What influences their acceptance of Distance Education?	646-667
Integrating generative AI with open educational practices (OEP) in an online learning environment: Perceptions of College instructors, Potentials, and Challenges	668-694
Leadership in Song: Developing Collaboration, Community, and Leadership Practices through Music in an Online Course	695-712
Promoting and evaluating professional learning among teachers through open online discussions	713-737

Introduction to the Special Issue: Higher Education in an AI-Transformed World

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Artificial intelligence (AI) has been evolving for decades. In the latter part of the 20th century and the early part of the 21st century, AI received modest interest on the part of the general public. At the time, it had been the focus of activity among computer scientists and technology specialists. The launch of OpenAI's ChatGPT in November 2022 brought significant global attention to this foundational generative AI (GenAI) platform. American corporations such as Alphabet (Google's parent company), Microsoft, Nvidia, and Amazon started investing billions of dollars in this technology. Internationally, well-funded companies in China such as Baidu, Tencent, and Alibaba began challenging American hegemony in AI development. The early GenAI programs such as ChatGPT, Claude, and Gemini are now evolving into broader general AI programs. In four short years, all walks of life including private industry, government, and education have begun developing and implementing AI applications.

In 2025, the editors of OLJ saw that the time had come to examine AI with respect to higher education, where its fast-moving integration has raised critical questions related to pedagogical, ethical, personnel, and technological issues. For this special edition, articles were solicited from faculty, researchers, and administrators who are using AI in higher education.

Definition of Terms

It is important to define and distinguish between the major forms of AI. AI is a broad field of science in which machines are taught to develop humanlike capabilities. General AI occurs at the point when AI can learn human cognitive skills (Suleyman, 2023) and is rapidly developing. A more recent term, "agentic AI," has come into use and is related to general AI. The primary difference between the two is that agentic AI is a more specific application. It is proactive, autonomous, and adaptive, capable of planning, reasoning, and taking specific complex actions independently to achieve objectives in dynamic environments.

While general AI and agentic AI are in early developmental stages, GenAI (such as ChatGPT) is currently in widespread use. It is a technology within the field of artificial intelligence that utilizes "neural" networks which mimic the human nervous system to create new and original content. It can produce a wide variety of data, including text, images, audio, and video. GenAI can also create content such as synthetic data, code, simulations, and more by identifying patterns and structures within existing data. GenAI builds upon technologies like large language models (LLMs), which are trained using vast amounts of data, to predict and develop new data such as original images or text structured in sentences and paragraphs. GenAI programs such as ChatGPT, Claude, and Gemini are being used routinely by everyday people to

find basic information, to develop ideas, and to engage in creative activities. College faculty and students are embracing GenAI for lesson planning, writing assignments, and collecting background information on topics of interest. In summary, GenAI is now commonly utilized and considered for use in a wide variety of activities. As one author in this special edition concluded, the central question facing educators today is not “What will AI do?” but “What will AI *not* do?”

With these distinctions in mind, what follows is a brief review of the articles included in this special edition generated in part with assistance from the GenAI program, Claude.

In “Artificial Intelligence and Digital Learning: Architecture, Hallucinations, Information, Findability, The First Rung, and The Arts of Inquiry,” Gardner Campbell, Charles Dziuban, Colm Howlin, and Mark Smith offer a wide-ranging conceptual examination of how AI powered by large language models (LLMs) is reshaping education, the workforce, and human cognition. The article begins with an accessible explanation of transformer architecture, tokenization, and the hallucination problem before turning to a compelling argument about information structure. Drawing on scale-free networks and power law distributions, the authors contend that AI has become the dominant “hub” in the information ecosystem, fundamentally shifting learners from active seekers to passive recipients of algorithmically served answers. Most urgently, they introduce the concept of the “disappearing first rung”—the AI-driven erosion of entry-level jobs that have traditionally served as the formative training ground where new graduates learn to think, navigate ambiguity, and develop professional judgment in real-world settings.

In “Understanding the Generative AI Divide: Faculty and Student Perspectives in Higher Education,” DeStefano, Hackney, & Moskal report findings from a large-scale survey of 3,164 students and 166 faculty at the University of Central Florida, examining actual GenAI usage patterns, perceptions, and training needs. Despite 88% of students reporting familiarity with GenAI, almost half were not using it for academic work, and 76% had received no formal classroom instruction on its use — a striking gap the authors call the “familiarity-usage paradox.” Faculty showed similarly high familiarity but inconsistent integration, with only 33% encouraging students to explore GenAI tools and just 18% teaching students how to use them, barriers driven largely by concerns about academic integrity, student overreliance, and their own comfort with the technology. The study’s most consequential finding is the significant divergence in how the two groups perceive GenAI’s impact on learning: students were decidedly optimistic ($M = 4.0/5.0$) while faculty were skeptical and fell below the neutral midpoint ($M = 2.8/5.0$).

In “Graduate Teacher Education Students Evaluate Generative AI – A Two-Year Comparison,” Anthony Picciano presents a qualitative longitudinal study tracking how 45 experienced K-12 teachers enrolled in a graduate education leadership program at Hunter College changed their views and use of GenAI between Spring 2023 and Spring 2025. Using student essays and focus group discussions as data sources, the study finds a dramatic shift over just two years: in Spring 2023, only one of the fifteen participating students had previously used GenAI, and seven students declined the AI assignment entirely; by Spring 2025, nearly all students were using it regularly, with many reporting that their school districts had proactively organized professional development workshops around tools like Magic School AI and Toddle

AI — purpose-built teacher platforms. Three thematic comparisons anchor the findings. First, teachers in 2025 had moved from speculating about AI’s potential to documenting its active use in lesson differentiation, IEP goal-writing, report card comments, and curriculum planning. Second, both cohorts were particularly enthusiastic about AI’s applications for special education students and English language learners — but by 2025, teachers could describe specific, concrete classroom implementations rather than hypothetical benefits. Third, while 2023 participants drew simple grade-level lines around student AI use (generally permitting it in high school, dismissing it for younger grades), 2025 participants expressed more nuanced and cautious positions, wrestling openly with concerns about cognitive development, critical thinking atrophy, over-reliance, and the difference between AI enhancing versus replacing student thinking. Picciano concludes that teachers have become meaningfully more sophisticated in their AI literacy.

In “The Promise and Paradox of AI in Doctoral Education,” Brown and Shelton propose a conceptual framework for integrating AI as an adaptive support system in doctoral programs, addressing the persistent problem of student isolation and attrition during the dissertation phase. Grounded in Vygotsky’s sociocultural learning theory — particularly the Zone of Proximal Development and scaffolding — the framework reframes doctoral independence as “supported autonomy”: the ability to direct one’s own research while strategically leveraging available resources, including AI tools. The model organizes AI’s potential contributions across three interconnected dimensions. Cognitively, AI can serve as an always-available “critical friend” that helps students overcome writer’s block, refine arguments, and prepare more focused questions for supervisor meetings. Affectively, AI provides a non-judgmental space for testing ideas that reduces imposter syndrome and builds confidence through small, incremental successes. Socially, AI bridges the “scaffolding gap” that opens when coursework ends and structured support recedes, helping students maintain momentum and arrive at human mentorship interactions better prepared.

In “Curriculum Mapping as a Tool for Continuous Improvement of the Business Studies (BS) Curriculum in a Digital-First University,” Aldin Bellinfantie presents a theoretically grounded curriculum mapping framework developed for Arden University’s School of Business and Creativity, using its BA (Hons) Business Management program as a case study. Drawing on learning theories including Constructive Alignment, Cognitive Load Theory, and social constructivism, the framework adapts established models (particularly Veltri et al., 2011) into a five-step cyclical process that maps Program Learning Outcomes, Teaching and Learning Activities, and Assessment Methods against both internal institutional attributes and external benchmarks such as QAA Subject Benchmark Statements and World Economic Forum skills forecasts. The case study analysis reveals that while the program demonstrates strong vertical coherence — with concepts progressively scaffolded across levels — it suffers from weak horizontal integration, where critical skills like data analytics risk becoming siloed within individual modules rather than woven across the curriculum.

In “Predicting Online Instructional Design Students’ Intention to Use AI Tools: Value, Utility, and Self-Efficacy,” Cho and Chen report findings from a survey of 74 online instructional design (ID) master’s students at a U.S. university, examining what factors predict their intention to use AI tools in professional practice. Drawing on an extended Technology Acceptance Model (TAM), the study found that demographic variables — gender, age, and full-

or part-time status — were not significant predictors, while three attitudinal factors together explained 64.8% of the variance in students’ intention to use AI: the utility of AI tools for their own academic tasks (the strongest predictor), the perceived value of AI for student learning, and self-efficacy in using AI tools. Cluster analysis further revealed two distinct groups — a “highly positive” group (55%) scoring above average on all four measures, and a “less positive” group (45%) scoring below average — with qualitative content analysis showing that the highly positive group used AI more diversely, viewed it as a collaborative partner, and generated more constructive ideas about its role in instructional design. A significant contribution of the study is its differentiation of perceived usefulness into two distinct constructs, finding that students’ direct, personal experience using AI tools for their own tasks matters more than abstract beliefs about AI’s general pedagogical benefits — a nuance that has direct implications for program design.

In “Transforming Enrollment Management in the Field of Online Learning,” Vickie Cook presents a practitioner-focused roadmap for online learning administrators navigating the evolution from Business Process Mapping (BPM) through Business Process Automation (BPA) to fully AI-driven enrollment management. The article argues that BPM — the visual documentation of workflows across admissions, financial aid, and student communications — is the essential first step toward automation, and that BPA, while valuable for streamlining routine tasks and reducing manual errors, remains inherently limited: it cannot adapt in real time to individual student behaviors, respond to rapidly shifting enrollment conditions, or scale personalized engagement. AI, by contrast, offers three distinct capabilities that go further: predictive AI for forecasting yield and financial aid decisions, GenAI for hyper-personalized student communications, and agentic AI for autonomous workflow management including transcript review and recruitment optimization. The article’s central argument is that institutions must treat the BPM-to-BPA-to-AI pathway as a deliberate strategic continuum rather than a set of discrete technology upgrades, and that freeing staff from repetitive processing work allows them to focus on the high-touch human interactions that drive student success and retention.

In “Educating the Educators about AI: Strategic Initiatives in a Graduate School of Education,” Borasi and Fredericksen chronicle the Warner School of Education at the University of Rochester’s two-year initiative to build internal capacity around GenAI and redesign programs to prepare future education professionals for an AI-transformed workplace. Drawing on entrepreneurial frameworks and lessons from a prior online learning initiative, the authors describe how the school established an AI Task Force, hired a dedicated post-doc to track GenAI developments, engaged faculty through differentiated professional learning opportunities, and ultimately launched a new Advanced Certificate in AI for Educators and Helping Professionals. The article’s central argument is that schools of education must go well beyond debating whether students should be allowed to use AI — they must fundamentally rethink curriculum, assessment practices, and faculty development in light of AI’s growing role across all education professions.

In “Graduate Students at the Frontier of GenAI: Emerging Trends from a Southwest Borderland University,” Parra, Chatterjee, Okoye, and Lucero present findings from a qualitative survey of 24 graduate students enrolled in online educational technology courses at New Mexico State University, a Hispanic-serving institution. Drawing on Connectivism and the Concerns-Based Adoption Model (CBAM), the study traces how students moved from limited prior

exposure to GenAI to more purposeful integration, with close to 70% reporting at least weekly use and nearly all viewing it as helpful for teaching and learning. Three thematic trends emerged from the data: “promise, productivity, and partnership,” where students increasingly framed GenAI as a collaborative partner rather than a simple productivity tool; “boundaries and ethics,” with 83% expressing concerns about academic integrity and over-reliance; and “navigating uncertainty,” marked by inconsistent course-level policies and only 22% feeling their institution had provided adequate guidance. A particularly distinctive contribution of this study is its focus on students who are simultaneously practitioners — mostly community college faculty and K-12 educators — giving them a dual vantage point as both learners and instructors grappling with GenAI’s implications.

In “Asked & Answered: Using AI to Nudge Student Metacognition and Responsibility for Learning,” a team of faculty and instructional technologists at the University of Maryland, Baltimore County (UMBC) presents a reflective case study of four courses that share a common pedagogical goal — developing students as self-regulated learners — and are exploring AI as a tool to personalize and scale that effort. Grounded in Sandra McGuire’s framework for teaching metacognition through Bloom’s Taxonomy, the article describes how AI is being integrated differently across four distinct contexts: CHEM 102 uses spaced practice question banks to counter student cramming, with AI as a potential tool to help students eventually curate and schedule their own practice; SCI 100 asks students to crowdsource exam prediction questions for extra credit, with AI positioned to streamline curation and reduce faculty burden; UNIV 102 uses Team-Based Learning with AI-generated quiz questions to help academically at-risk students build study group skills and develop honest self-assessment habits; and CHEM 101 deployed a Google NotebookLM-based “Virtual Prof Bass” — trained on 36 course documents — that gives 800+ students 24/7 access to a patient, Socratic AI tutor modeled on the instructor’s own voice and approach. The article’s central argument is that the right question about AI in education is not how to prevent students from using it, but how to use it to deepen students’ willingness and capacity to honestly assess what they know and close their own learning gaps — a skill the authors frame as essential to becoming a lifelong, self-regulated learner.

We sincerely thank the OLJ copyeditors for their hard work at getting these articles to “press” as well as the OLJ Editor-in-Chief, Dr. Peter Shea, and Managing Editor, Dr. Carrie Miller, who helped us make this special issue a reality.

We hope that you find these articles helpful and that they inspire ideas on future uses of AI in higher education and beyond. If you are conducting research on the use of AI, please consider submitting your work and volunteering as a reviewer to help maintain the high quality of *Online Learning*.

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Artificial Intelligence and Digital Learning: Architecture, Hallucinations, Information, Findability, The First Rung, and The Arts of Inquiry

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Abstract

The authors address Artificial Intelligence (AI) powered by Large Language Models (LLM) and its relationship to learning in contemporary education. Initially they explain the underlying functionality of AI using transformer architecture, embedding, and tokenization to create language symbolism. Next, they discuss the transformed search concept and how scale-free networks and power law distributions portray information sources dominated by AI hubs that couple and decouple digital learning resources. They contend that Artificial Intelligence will replace bottom- and entry-level jobs by removing a foundational rung of new graduates' career development. This shift, termed the *answer machine*, will impact graduates, industry, and education, creating an urgent need to mitigate the risks and leverage the opportunities AI presents. Finally, they consider potential consequences to human creativity, insight, wisdom-related knowledge, and the arts of inquiry in an AI-driven world where we face the danger of losing the ability to think about thinking. Artificial Intelligence can lead to a remarkably improved culture of education. At this time, however, with our seriously limited understanding of its long-term implications, AI presents more questions than answers, so the immediate need is to suggest a context for the best-informed and most important questions to emerge and receive robust consideration at all levels of society.

Keywords: Artificial Intelligence; digital learning; information structure; entry level jobs; inquiry process

Campbell, G., Dziuban, C., Howlin, C., & Smith, M. (2026). Artificial Intelligence and digital learning: Architecture, hallucinations, information, findability, the first rung, and the arts of inquiry. *Online Learning*, 30(2), 1-30. <https://doi.org/10.24059/olj.v30i2.6050>

Introduction: How Artificial Intelligence Works

As Generative AI powered with Large Language Models (LLMs) impacts society, it becomes essential to understand the influence of architecture, training, and alignment processes. They can exert a profound and often undetermined influence on knowledge dissemination, education, and learning (AAC&U, 2025; AAUP, 2025; Dubois, 2024; Robert Ovetz, 2025). Therefore, understanding how these systems are constructed and address “knowledge and values” provides insight into their capabilities and issues. While avoiding excessive technical depth, this section provides an explanation about the core components and training procedures that underpin modern LLMs.

Transformers, Attention, and Embeddings

Most modern LLMs are built upon transformer architecture, a deep learning approach introduced in 2017 (Vaswani et al., 2017). The original development proposed an encoder-decoder structure. Here, we will concentrate on the decoder component because it is the element that powers the LLMs behind applications like ChatGPT and has fueled the generative AI revolution.

At its foundation, the model takes input text and creates an initial embedding through a process known as “tokenization” (Pilehvar and Camacho-Collados, 2021). This takes words and subwords and converts them into numbers. Short common words like “the” are usually single tokens, while longer or more complex words get broken into multiple pieces. For example, the word “understanding” might be split into “under” and “standing.”

After tokenization, each word gets converted into a vector or embedding. These are numeric representations of the token. Words and tokens that have similar meanings will have like numeric values, and words that are very different from each other will have different numeric positions. For example, we might expect “king” and “queen” to have similar values and “king” and “calculus” to be considerably different.

The models interact with these numeric tokens rather than the input text. The LLM processes them, much like we would read the words in the input text. As it processes (or reads) each token, it builds up a representation of what the text means. There are various mechanisms it uses for this, “self-attention” being the most prominent. Not all tokens in the sequence are equally important for understanding the current one under consideration and attention allows the model to understand which *previous* input elements are the most relevant to the *current* one and where it should focus. This self-attention mechanism is an important breakthrough in the development of LLMs, with the original paper titled “Attention is All You Need” (Vaswani et al., 2017).

Once it has read all the input tokens and established its internal representations, the final step assigns a probability to every possible next *token*. From here, it can select most likely candidates and assigns the next token in the sequence. There are several ways of selecting tokens from the candidates, with the highest probability being the simplest. Most models allow the introduction of some variation using a parameter known as “temperature.” This term is borrowed from the simulated annealing method that allows users to introduce some randomness into the

process. Many think of this as controlling the model’s freedom or “creativity.” The higher the temperature, the freer the model is to select from the most probable next candidates.

With the token selected, it is appended to the input, and the process is repeated to select the next one in the sequence. The model stops once it generates a special “EOS” or end-of-sentence token. Fundamentally, a Generative Model repeatedly predicts and appends tokens in a sequence.

Pre-training and Fine-tuning

The above section outlines what the process does, but input data trains the model to do this. These mechanisms have thousands, millions, and increasingly billions of associated parameters. Each one controls some aspect of how the model functions. With so many parameters, it is impossible to understand or specify them. The only way they can be set is for the model to “learn” them from data in the training process.

The sequence begins by setting the parameters at random. Then, by supplying inputs and comparing them to expected outputs, the parameters are adjusted by the training process so that the predicted output is brought closer to the expected result. This is repeated over *trillions* of tokens to train the largest models. For modern prompt-driven LLMs, the process is typically broken down into a two-stage training paradigm: pre-training and fine-tuning.

Pre-training is the initial, computationally intensive phase where the model learns general language understanding, grammar, common sense knowledge, and world facts. This is achieved through “self-supervised learning” (predicting the next or missing token/word) on vast, diverse datasets, often comprising trillions of tokens scraped from the internet (Guo et al., 2024). The output is called a pre-trained model. It can understand the inputs in the languages it was trained in, and it can predict the next token, but it cannot reliably accomplish more complicated tasks that we see modern LLMs achieve. That is where fine-tuning enhances the process.

Fine-tuning involves the pre-trained model being adapted or specialized for specific downstream tasks. Typically, this involves further training on smaller, more curated, and often labelled datasets relevant to the target application. Generally, these tasks are more complex (such as writing code or summarizing a document) (Xia et al., 2024).

Recently, a special class of fine-tuning has emerged called Reinforcement Learning from Human Feedback (RLHF). In this variation, the dataset used to fine-tune the model is based on human preferences (Zhang et al., 2024). This has been shown to increase the quality of outputs dramatically. However, a key point is that RLHF aligns the model to produce outputs humans prefer, not necessarily with factually correct answers. The system learns to replicate judgments made by these individuals (Liu, 2023), potentially introducing hidden biases.

Reliability: Errors and Hallucinations

A significant challenge for the use of LLMs in all applications, and in particular education, is “hallucinations.” This is the LLMs’ tendency to generate inaccurate or entirely fabricated information (Meade and Jano, 2024). This issue is attributable to fundamental design

and training and poses considerable risks in settings where factual accuracy and trustworthiness are paramount.

Hallucinations can sometimes be obvious and caught by users; however, in contexts where the user has insufficient knowledge about the subject or task at hand, identifying these mistakes can be difficult, if not impossible. Often, this is the case with students' use of Gen AI. Coupled with the confidence with which these models speak, the results appear plausible and coherent but can be factually incorrect, nonsensical, irrelevant, or entirely fabricated (AAUP, 2025; Guo et al., 2024).

Several factors contribute to the occurrence of hallucinations:

1. The vast datasets used for pre-training inevitably contain errors, biases, outdated information, and inconsistencies.
2. Incomplete data on certain topics can also lead models to “fill in the gaps” with plausible but incorrect information (Guo et al., 2024), due to the RLHF fine-tuning goal to generate an output humans like as opposed to one that is correct.
3. This probabilistic generation process inherently allows for deviations from factuality (Guo et al., 2024).
4. A process known as overfitting (putting too much emphasis on specific patterns in the training data) can also contribute (Guo et al., 2024).
5. Most LLMs lack direct access to real-time information or a continuously updated external knowledge base (Zhang and Zhang, 2025). Its knowledge is essentially frozen at the time of training.
6. Ambiguous or poorly phrased prompts can lead the model to misinterpret the user's intent and generate irrelevant or incorrect responses (Guo et al., 2024).

Despite the ongoing efforts of developers to address these issues, hallucinations persist, leading some researchers to contend that they might be an inevitable structural feature of current LLM architectures (Banerjee et al., 2024).

Rapidly Developing Evolvment

Advancements on the horizon could significantly impact and strengthen the impact of AI. The trend expands past purely text-based towards multimodal models, capable of processing and generating text, images, audio, and video (Wadkar et al., 2024), with the possibility of personalizing content for learners.

Another key development likely to impact all Gen AI use is the work to improve model reasoning. This is sometimes referred to as “emergent” in LLMs, since it wasn't trained explicitly into the model but emerged due to the training data and architecture (Berti et al., n.d.). Developers are working to improve this capability with future iterations expected to exhibit more sophisticated logical thinking, enabling them to solve complex problems, understand cause-and-effect relationships, and make more informed decisions. This includes advancements in areas like multi-step reasoning, where the AI can break down a problem into smaller parts (Wang et al., 2024), and counterfactual reasoning, where the AI can understand “what if” scenarios (Alihan et al., 2025).

Another significant trend in the development of reasoning is the rise of Agentic AI, where systems move beyond passive responses to take proactive actions and make autonomous decisions (Purdy, 2024). The models use their reasoning capabilities to break down problems and arrive at results. The agent can function with a human in the loop or completely autonomously. Many industries have these autonomous agents in production, with several well-known examples such as Deep Research from OpenAI (Openai.com, 2025), and Manus (Manus.im, 2025). At the moment, the future of Artificial Intelligence appears unbounded, and progressing at a pace rarely encountered in the history of evolving technology.

Ambient Findability: Information Wayfinding in the Age of Artificial Intelligence

Twenty years ago, Peter Morville published *Ambient Findability* (2005), a definitive resource for information search and curation. He explained that findability coalesces navigation, labelling, and information architecture into a comprehensive knowledge acquisition model:

1. The ability to navigate and find information in a saturated environment.
2. The necessity of information literacy to evaluate unfiltered data.
3. Understanding the disproportionate distribution of information.
4. Understanding that information constitutes a complex network that cannot be readily disaggregated.

Additionally, he integrated the notion of “wayfinding” where search moves from one source to another in an iterative progression.

Wayfinding is a fancy word for a series of things people know and do to get from one place to another, inside or outside. Wayfinding can be a snap or an onerous task, depending on the person, the environment, and the situation. You can think of wayfinding as a five-step process. It starts with knowing where you are. It means knowing your destination, following the route to your destination, being able to recognize your destination and finding your way back to your starting point (Morville, 2005, p. 17).

Wayfinding is an accurate description of our contemporary educational environment. Teachers orient their way through their courses no matter how organized they are at the onset. Students orient their way through those same courses and together education becomes more than the sum of its individual parts like the emergence and self-organization of complex systems. However, modern information communication technologies, by interacting with each other, reframe Morville’s definition of wayfinding by limiting human involvement (Floridi, 2014). This relates to the Bates (1989) berry-picking search that is a non-linear search paradigm and corresponds to Wikipedia—the democratic information source that features open editing and continuous updates. According to Morville, the core principle of ambient findability is its potential for making information available anywhere at any time.

Although the book was an authoritative resource at the time, one of its significant contributions was its resonance with literature such as the chestnut tree in *Jane Eyre* (Brontë, 1847), the green light in *The Great Gatsby* (Fitzgerald, 1925) and the train in *Anna Karenina*

(Tolstoy, 1878), foreshadowing what was to come in the world of ubiquitous connectivity. However, the notion of foreshadowing becomes difficult in the context of artificial intelligence that is developing at an exponential rate, although that growth will moderate much like population growth modeled by the logistic map.

Morville did acknowledge the growing search potential of artificial intelligence (AI). However, today we find ourselves working with systems that alter how we engage with knowledge. We no longer actively search because information is served up as we ask by a metaphorical ATM. In the hyperconnected AI environment, the boundary between machine and human intelligence is blurring and changing what it means to know something (or even how). Our interaction becomes less mindful because we cede considerable human control to automated mediation. As a result, we live with a knowledge environment that must balance accessibility with intellectual agency.

Scale Free Networks and Asymmetric Power Law Distributions: Why They Matter

Contemporary science and technology influence every aspect of our lives. One effect is the formation of networks: for example, the internet, mobile phones, and social media (Harari, 2024). The most influential, however, are scale-free networks that develop as self-organizing entities in the absence of a central controlling mechanism (Caldarelli, 2007; Mitchell 2009). They feature a small number of hub nodes with many connections while most other nodes have far fewer pathways. Airline networks exhibit scale-free characteristics, as do social media sites where influencers dominate the connections. One explanation is the preferential attachment phenomenon where nodes entering the network connect to already established hubs (Barabási, 2016). Scale-free networks are remarkably resilient and information spreads rapidly throughout them. Additionally, they provide insight into the functioning of complex systems like the internet. However, the most important characteristic of these structures is that they conform to a power law distribution, sometimes called the long tail, where there is a piling up of occurrences on the left side with a steep decline going to the right (Newman, 2005; Anderson, 2006; Dziuban et al., 2023). This represents the marked asymmetry in the distribution of information (Taleb, 2007; Taleb, 2012; Taleb, 2018). There are multiple examples:

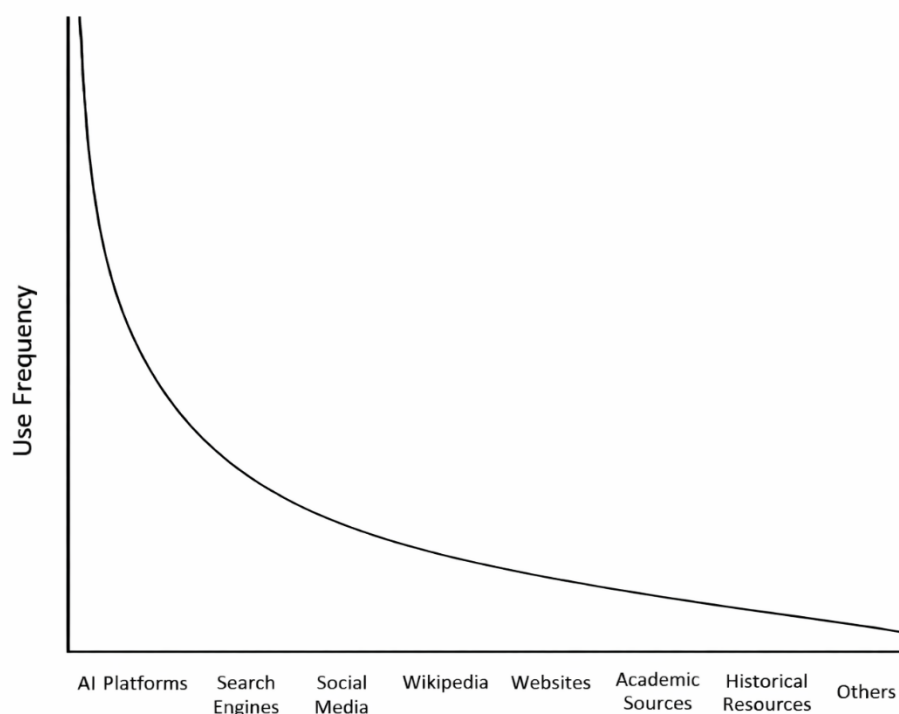
1. city populations
2. incomes
3. the size of corporations
4. word frequency in languages (Zipf, 1949)
5. internet traffic
6. academic article citations

In science, network thinking provides a novel language for expressing communalities across complex systems in nature, thus allowing for insights from one area to influence other, disparate areas. In a self-referential way, network science itself plays the role of hub—the common connection among otherwise far-flung scientific disciplines (Mitchell, 2009).

The question becomes then how do scale free networks and power law distributions relate to teaching, learning, and information search in the world of ambient findability, wayfinding, and artificial intelligence. If one examines the use of contemporary information sources, their distribution conforms to the scale-free power law. Consider Figure 1.

Figure 1

A Thought Experiment for the Power Law Distribution of Information Sources



If this thought experiment is correct, it represents a shift in the information process—that is, the information seeker becoming more passively receptive. The emergence of large language models as the dominating information source represents what Gladwell termed a tipping point (Gladwell, 2024), Kuhn labeled a paradigm shift (Kuhn, 1962), and Page identified as a phase transition (Page, n.d.). Examining figure one, we see that the flatter part of the curve represents a more slowly evolving search process. However, as the curve begins to accelerate, we see a rapid transition from Wikipedia to AI. The power law information source curve has two other noteworthy characteristics. Firstly, the sources listed on the horizontal axis are general prototype categories that denote large numbers of subcategories. Secondly, the graph is a static representation of dynamic processes where the categories change order or appearance, but on the left side of the horizontal axis the dominance of AI is unlikely to change soon. Figure 1 changes the adage “knowledge is power” to “the ability to use knowledge is power”—a dramatic transformation in the educational landscape. However, the modal portrayed in figure one is not yet validated and therefore should be considered a hypothetical construct that requires long term rigorous assessment and verification. That said, there are examples of this delayed validation in

science: general relativity, the Higgs field, natural selection, continental drift, the cosmic microwave background, and exoplanets. Delayed validation is also the case in education and learning theory: for example, constructivism, critical period for language learning, mastery learning, and spaced repetition.

Artificial Intelligence and a Restructuring of the Information Framework

The seed of the current revolution is the computer. Everything else from the internet to AI is a byproduct. (Harari, 2024, p. 193)

Future generations will never know what an exclusively analogue, pre-digital reality was like. We are the last generation to have experienced it. (Floridi, 2019, p. XI)

These quotes from two leading thinkers in artificial intelligence either foreshadow the future or document the history of the information age. As Harari (2024) describes historical perspective, the narrative of history often becomes more important than the actual event. For instance, Rosa Parks and the Montgomery bus boycott, Paul Revere's ride, or Rosie the Riveter. These events were important in and of themselves but pale in comparison to the narratives that developed in the years following them. Acknowledging the long developmental history of large language models, in a remarkably brief time, the narrative has far surpassed a single event like the release of ChatGPT. The story of artificial intelligence has developed so rapidly that something remarkable has happened. Eric Hoffer, an American dock worker and moral and social philosopher, wrote about the nature of what he termed mass movements and the psychology of individuals within them. In his book "The True Believer: Thoughts on the Nature of Mass Movements" (1951), Hoffer describes "believers," a type we now find among those who are deeply involved in a movement like large language models. The pervasive media reach heightened by global interconnectedness accelerates the worldwide conversation, enthusiasm, skepticisms, and curiosity about artificial intelligence. The narrative is ubiquitous, compelling, and dominating.

Coupling and Decoupling

Floridi (2019) describes the process thus:

The digital "cuts and pastes" our realities both ontologically and epistemologically. By this I mean that it couples, decouples, or recouples features of the world (ontology) and therefore our corresponding assumptions about them (epistemology) that we thought were unchangeable. It splits apart and fuses the 'atoms' of our 'modern' experience and culture so to speak. (p. 6)

Although Floridi addresses and emphasizes artificial intelligence, note that he casts it in the context of the digital—the implication being that AI is coalesced with other aspects of information communication technologies and draws upon them for its training protocols. Although it may appear as if one interacts uniquely with an AI platform, i.e., GPT Plus, there is an entire digital network in the background.

Some digital and AI decouplings:

1. intelligence and agency
2. location and presence
3. creation and authorship
4. diagnosis and expertise
5. experience and expertise

Specifically in education:

1. location and learning
2. time and learning
3. instructor and content delivery
4. libraries and information access
5. student engagement and instructor involvement

Some digital and AI decouplings:

1. diagnosis and expertise
2. algorithms and action
3. virtual and physical environments
4. pattern recognition and discovery
5. data analysis and human bias

Specifically in education:

1. instructor and student feedback
2. assessment and real time feedback
3. faculty development and teaching innovation
4. research collaboration across disciplines
5. curriculum design and skill development

Metaphorically, AI has “split the education atom” and shown that long held assumptions and actions can be separated or combined and in doing so may or may not improve teaching and learning. We may be sure, however, that the coupling or decoupling of these familiar structures will be disruptive. Moreover, in a complex system such as education, it is impossible to anticipate how an intervention will ripple through it. Often the outcomes will be counterintuitive and there will be unanticipated positive and negative side effects, all of which must be accommodated.

The Adjacent Possible for Education

The impact of artificial intelligence on education is undeniable but prediction for the long term becomes difficult because a proper baseline is so elusive (Rosling et al., 2018; Johnson, 2014; Roberts, 2007). Consider the protagonist Clay’s response to predicting the future in the book *Mr. Penumbra’s 24-Hour Bookstore* (Sloan, 2013):

World government...no cancer...hover-boards.
Go further. What’s the good future after that?
Spaceships. Party on Mars.
Further.
Star Trek. Transporters. You can go anywhere.

Further...

I pause a moment, then realize: I can't. We probably just imagine things based on what we already know, and we run out of analogies. (p. 60)

However, there are foreseeable near-term implications for artificial intelligence in contemporary education. Driven by AI, customized learning paths can be integrated into the curriculum. This can be augmented with increased accessibility and interactive learning. There are other possibilities, such as better student and faculty collaboration or retention support. In the larger context, large language models will offer a wide range of educational assets that can relieve teachers and students from routine educational tasks and support more effective educational systems, while accommodating the necessary responses to societal changes.

At the same time, education will face AI challenges. One of the most concerning is the overreliance on platforms producing metacognitive laziness—reducing insight, creativity, and curiosity. The effect of something like Maxwell's "demon" (Maxwell, 1871) might convince students that knowledge can be gained and learning accomplished with no work involved. Just as physicists dispatched the demon by showing that gaining information involves work, the same is true for learning. There are other challenges—for instance, inherent bias in platforms acquired during their training protocols. Dickens was foreshadowing AI when he described a period of revolution as the best and worst of times (Dickens, 1859). For instance, our new understanding of interaction will be that of continually reframing our prompt queries because of the misalignment between what we thought we asked, and what AI responded to because it lacks contextual understanding.

Einstein and Carroll: Special Relativity and Individually Paced Learning

Similar principles apply in physics and education. In 1905, Albert Einstein's monumental thought experiment, special relativity, showed that the speed of light in all frames of reference under uniform motion is constant (Stoddard, 2023). Therefore, because of this constancy, the observed time must expand or contract. It dilates for speeds relative to the observer—meaning that for different reference positions time must be experienced differently to reflect light's constant speed (French, 1968; Billstrom, 2024). In 1963, John Carroll applied the same principle to education (Carroll, 1963). He showed that if learning is constant, then the time required must be flexible just as time is in special relativity. Students learn at different rates, so rather than place them in fixed time circumstances, such as semesters, students that require more time should be given it and those needing less should be accommodated. Again, learning time varies from the reference frame of the observer—student or instructor. Both Einstein and Carroll, in completely different contexts, arrived at the same conceptual conclusion that when one aspect of an environment is constant (light in physics and learning in education), another, such as time, must compensate. The principle supports adaptable approaches to education where instructional time flexes to ensure student mastery just as time bends in special relativity to accommodate light. In the education space, AI is likely to play a key role in bending learning time.

The Disappearing First Rung: How the Answer Machine Will Replace Entry Level Jobs and Impact Education and Organizations

Generative AI and related modern technologies will significantly change and in many cases replace entry-level jobs for higher education graduates, removing a foundational rung in new graduates' career development. Understanding how this shift will impact graduates, organizations, and education alike is essential to mitigate the risks and leverage the opportunities it creates for all three groups.

The chapter "Sprint to 2027" in Moskal et al. (2023), describes how one technology company is preparing for the shifting speed and scale modern technologies brings to its organizational culture. These rapid developments create an urgent need for a strategy to upskill the existing workforce while reshaping the methods and processes employees use to learn, think, and problem-solve. That argument is taken at least one step further given how Generative AI has dramatically escalated the technological impact on the workforce. The implications AI has for entry-level jobs that are traditionally the training ground for new graduates learning how to think in real-world environments creates a disappearing first-level career ladder rung. These roles, although often not glamorous, were formative. However, by 2030 a substantial share of roles in areas such as data entry, customer service, telemarketing, and financial and business analysis will be significantly reshaped by automation of routine tasks and AI-augmented work (World Economic Forum, 2023; McKinsey Global Institute, 2023; Forrester Research, 2024). In fact, it has already started: by late 2025 overall hiring had weakened. This weakening was mostly in tech and knowledge-work roles such as marketing and human resources, but job postings explicitly mentioning AI continued to grow, likely signaling a reallocation of hiring toward AI-related capabilities rather than broad employment expansion (Indeed Hiring Lab, 2026). The short-term cost efficiencies of Gen AI technologies are too attractive for commercial enterprises to resist even if they negatively impact long-term talent development.

The decrease in entry level jobs means new graduates will have fewer opportunities to start in roles where they confront ambiguity, gather information, and observe how decisions are made in interpersonal settings. Unfortunately, these experiential knowledge and skill sets are not readily acquired in classrooms, and increasingly less so post-COVID (Legon et al., 2023). However, if educational institutions collaborate with employers to reimagine workforce preparation where employees are fluent in enabling and leveraging AI, new graduates will be better prepared by being able to apply more critical thinking skills and fill higher-functioning roles beyond the traditional entry-level first rung positions.

Workplace Impact: The First Rung Will Disappear

In the traditional organizational model, new entry level employees with higher education degrees used their roles to gain fluency in complex, often ambiguous work environments. These proving grounds were where they gained, practiced, and refined critical thinking skills, eventually developing competence. However, increasingly, students use the generative AI embedded in standard software like Microsoft Office apps. While AI use has dramatically improved the polish and style of students' output, it often belies a cognitive disengagement from the subject matter, and frequently results in writing that is generic, hackneyed, and often easily recognizable as AI slop. Put another way, they understand the form of what is being written and

some of the context while expecting the polish AI provides, but they do not deeply understand the underlying concepts. In a professional development context, this is a missed opportunity to develop a deeper understanding of the subject area in which they are working and develop the employee's individual style and persona.

Hard to Find Skills and Economic Drivers

Consistently over the past decade, in North America and Europe, employers reported in surveys that critical thinking, problem-solving, and analytical reasoning are among the most highly valued skills, they are also the most frequently lacking in recent graduates. In a 2020 AAC&U survey, sixty percent of employers said critical thinking was “very important,” yet only thirty nine percent believed graduates were very well prepared. That twenty-one-point gap has been stubbornly consistent. Put simply, employers want people who can question, synthesize, evaluate and who can make sense out of ambiguity. But if higher education institutions are only modestly successful at developing these skills, what happens when the early career roles that functioned as training grounds are themselves automated?

Strong Economic Incentive for AI

According to McKinsey (2023), generative AI could add up to \$4.4 trillion annually in economic value across sectors by making processes less capital intensive and more cost efficient. In both manufacturing and service industries, adopting AI is already showing measurable cost reductions. Almost thirty percent of the business leaders McKinsey surveyed in 2024 reported using AI to directly cut costs. From customer support to data analysis and other entry-level functions AI systems can now perform work that used to be assigned to new graduates—often faster, cheaper, and without the cost of onboarding employees while leveraging the economies of scale AI technology provides. This rational economic behavior is reshaping how and when people learn to think professionally. The risk is that a generation of graduates will find themselves not only displaced from these roles but also underprepared for the kinds of judgment intensive work AI still cannot do while employers will not have the supply of human talent needed.

What is often missing from this discussion is a cost-benefit analysis of what organizations lose by eliminating those early-career positions. These first rung jobs are pathways to long-term talent development and part of how organizational knowledge, values, and culture are passed on. Without a first rung, organizations risk undermining their own talent pipeline, especially in roles that require collaboration and ethical and contextual decision-making. Additionally, there is a secondary motivation for enterprises and even governments to delegate decisions to algorithms and systems so that the institution may be judged more leniently in the event of a bad outcome (Feier et al., 2021).

While workplaces are replacing entry-level roles with AI, educational institutions are grappling with AI's impact on learning.

Learning with the Answer Machine—Educational Institutions

In parallel with workplace adoption, students are increasingly using generative AI tools like ChatGPT to complete their academic work. The research on what this does to learning outcomes is still emerging, but increasingly troubling patterns are becoming more visible. A

randomized controlled study from Peking and Monash Universities (Fan et al., 2024) found that while ChatGPT helped students improve essay scores in the short term, it did not increase knowledge transfer or intrinsic motivation. More concerning, it triggered a form of what the researchers call “metacognitive laziness”—a diminished ability to monitor, evaluate, and adjust their thinking processes when AI is always ready to suggest the next move (Fan et al., 2024). This aligns with earlier research on “cognitive offloading,” where the brain delegates problem-solving to external tools. That can be helpful when navigating complexity but damaging if it becomes habitual (Risko & Gilbert, 2016). As psychologist Adam Alter put it: “Disfluency, the sense that something is hard, is often the trigger for analytical thinking” (Alter et al., 2007). When that friction is removed, so is the cognitive workout that builds real capability. Similar dynamics in studies on navigation have found that when people rely solely on GPS or digital aids, their ability to form mental maps and understand spatial relationships diminishes. In one study, users of digital navigation aid performed worse on wayfinding tasks and spatial recall than those who navigated unaided (Parush et al., 2007). Technology got them to their destination, but it did not teach them how to get there.

Prohibiting AI Is Not the Answer

Institutions respond by prohibiting and trying to detect AI-generated text. This response will fail for the same reasons prohibiting calculators from primary level education was unsuccessful. Arguably, it is more beneficial for students to learn mathematical reasoning rather than calculation skills (University of Oxford, 2012). Finding the right balance is a lesson learned from calculator prohibition experience. In any case, AI detection tools are the lie detectors of our time. AI detection software is documented as unreliable, prone to false positives and fundamentally reactive (Yuan et al., 2023). More importantly, AI detection tools do not address the core issues of learning. Students are using AI not only to cheat, but to cope with performance expectations, information overload, the pressure to do research quickly and the need to feel competent. Even more troubling is recent research showing that one third of teenagers are using Generative AI for companionship that is very sycophantic (constant validation, agreement) in a way that the authors posit stunt emotional regulation that does not allow teens to learn to think critically when someone questions their assumptions (Robb et al., 2025).

If Gen AI coping mechanisms undermine long-term mental and emotional growth, the solution is not punitive detection but a reframing of AI use much like how calculators were eventually integrated into education. Concurrently, policymakers must enact age-appropriate guardrails in primary education that protect them from technology that inhibits the development of their cognitive abilities and emotional coping skills that are foundational to success in the work environment.

Reframing AI in Learning

The question is not how to stop students from using AI, it is how to change education so that AI becomes part of and improves the learning process rather than a substitute for it. There are increasing examples of this reported in the press (Silber, 2024) as well as in cases where when resources are applied AI improves outcomes (Powell, 2024). Using AI to improve outcomes requires a reframing as a thinking partner or tutor rather than an “answer machine.” Scholars like Holmes et al. (2022) have begun recasting AI as an augmentative tool that can

support metacognition if used reflectively. This requires reframing the “answer machine” to being a Socratic dialog that encourages self-reflection.

To achieve this, educational institutions should consider:

1. Reward reasoning and problem-solving more than output.
2. Require reflection on the use of AI tools—how they help, what they and students miss when using them.
3. Teach students to interrogate AI content for bias, incompleteness, and oversimplification.
4. Shift grading away from polished correctness and toward documented process.
5. Implement age-appropriate guardrails to ensure cognitive and emotional development occurs optimally.

Without this shift, we risk graduating students who can prompt AI but not think beyond it.

Where to Start

Given the pace of AI development, there is a narrow window in which to respond. Employers will need to articulate the skills they need, and how they will help develop them in a changing work structure. Universities will need to move beyond content delivery towards intentional incubators of cognition. And educators must resist the temptation to see AI only as a threat or a tool in a binary sense; it is a medium, and like any medium, it shapes how we think. How can employers and universities share responsibility for redesigning this new learning-to-work transition? The answer is not clear, but more conversation, research, sharing of needs and practical approaches to developing skills are good first steps.

Balanced approaches are emerging across educational institutions in Europe and the United States. Current research highlights both the potential benefits and challenges of generative AI, while simultaneously outlining balanced strategies for progress (Vieriu et al., 2025)

Perhaps AI skills will develop naturally, and students will focus on content more than form (e.g., skipping menial work) and critically engage with context. The answer machine will keep improving and doing more than humans. The analogy to tellers replaced by ATMs and internet banking is obvious but AI will do more. However, unless we deliberately intervene soon it will do more than replace the first rung on the career ladder. It will hollow out the human readiness those jobs once cultivated for a coming generation and over time it will erode the human capital that enterprises need to be profitable.

AI and The Arts of Inquiry

The will to learn is an intrinsic motive, one that finds both its source and its reward in its own exercise. The will to learn becomes a ‘problem’ only under specialized circumstances like those of a school, where a curriculum is set, students confined, and a path fixed. The problem exists not so much in learning itself, but in the fact that what the school imposes often fails to enlist the natural energies that sustain spontaneous learning—curiosity, a desire for competence, inspiration to emulate a model, and a deep sense of commitment to the web of social reciprocity. Our concern has been with how those energies may be cultivated in support of school learning. (Bruner, 1966)

The condition for understanding the Truth is like the capacity to inquire for it.
(Kierkegaard, 1846)

A Mind at Work

Vannevar Bush's seminal essay "As We May Think" (1945) identifies two enormous difficulties faced by scientists: knowledge that is obscure or cannot be found, and knowledge that cannot be put to use because the pace of discovery outruns our minds.

AI can help with both of those problems. When Bush describes the "growing mountain of research" that leaves investigators "staggered by the findings and conclusions of thousands of other workers ... conclusions he cannot find time to grasp, much less to remember, as they appear," we can gratefully turn to AI summaries as one possible solution. When Bush analyzes "methods of transmitting and reviewing the results of research" that are "totally inadequate for their purpose," he offers the chilling example of Gregor Mendel's genetics research: "lost to the world for a generation because his publication did not reach the few who were capable of grasping and extending it" (p. 37). Here AI-enhanced searching brings hope.

Yet, as Bush describes the need to avoid "truly significant attainments becom[ing] lost in the mass of the inconsequential" (p. 37), we should recall that *significant* and *inconsequential* are value judgments best crafted not *for* our species but *by* our species, the species that searches for meaning. AI has the unwelcome potential to ease the burden of discernment onto its stout and confident mechanical shoulders, with the disastrous result that human beings will accede to a world in which their search for meaning becomes merely an acceptance of proliferating algorithmic judgments delivered by convincingly modulated pseudo-human voices, both oral and written. And we won't know it's happening, or even that it has happened.

Automatic machine-generated judgments, however, are only part of the risk our species faces with these new technologies. Perhaps the greatest risk of all is the loss of the arts of inquiry. How do we imagine the role of a question, and in turn, the character of an answer? Data may be served up like cash from an ATM, but the search for insight and fresh understandings depends on far more complex, provisional, and courageous modes of inquiry. As various kinds of AI increasingly constitute not only popular culture but the culture of education itself, the stamina and imagination such modes of inquiry require may recede into the past and ultimately be lost.

For Bush's vision in "As We May Think" is not limited to findability and curation. His vision is also one of sharing intellectual *exploration*. His focus at the climax of the essay shifts to collaborative knowledge generation fostered by shared histories of investigation. Bush's famous "Memex" was not just a "memory extender" but a means of recording and sharing what Bush called the "associative trails" marked by embodied minds as their inquiries take them hither and yon to the novel insights their wandering, varied lives empowered. Indeed, Bush called for "a new profession of trail blazers, those who find delight in the task of establishing useful trails through the enormous maze of the common record. The inheritance from the master becomes, not only his additions to the world's record, but for his disciples the entire scaffolding by which they were erected" (p. 46). These trails are not formulae or algorithms, repeating the same set of approaches uninflected by fresh experience (machines do not have experiences, merely

reactions), but the paths of thought, imagination, and idiosyncratic associations that together constitute a master class in the arts of inquiry. The trail blazer, in sum, “builds *a trail of his interest* through the maze of materials available to him” (p. 46, emphasis added).

Bush’s Memex thus becomes a moving picture of the mind at work in unpredictable ways that, inflected by personal experience and a stockpile of proximal and potential connections, may break through the “already” into “not yet.” Anyone blessed with a great teacher recognizes that an essential part of learning is attending to, and mulling over, the drama of inquiry present in the teacher’s articulation of knowledge, a drama all the more powerful for being suggestive rather than prescriptive. This drama of inquiry is what Michael Nielsen (2012) describes in *Reinventing Discovery: The New Era of Networked Science*: “It’s not just the scientific content that matters, it’s the culture that is revealed, a particular way of viewing the world.... [T]he first time in my life that I heard a scientist speaking informally was when I was 16. It changed my life” (p. 168–169).

Integrated Domains and Oblique Strategies

One of the most far-seeing prophets of the digital age in this regard was Douglas Carl Engelbart. Most famous as the inventor of the computer mouse, Engelbart’s accomplishments far outstrip that innovation, extending to a comprehensive vision of enhanced communication and collaboration in complexly linked networks. In his 1962 manifesto *Augmenting Human Intellect: A Conceptual Framework*, Engelbart prefaces his long and dazzling argument with this challenging statement:

We do not speak of isolated clever tricks that help in particular situations. We refer to a way of life in an integrated domain where hunches, cut-and-try, intangibles, and the human “feel for a situation” usefully co-exist with powerful concepts, streamlined terminology and notation, sophisticated methods, and high-powered electronic aids. (p. 1)

Engelbart understood, as only a small handful of people did at the time, that networked digital computing represented a fundamental change in the way human beings represented and communicated about their experience of the world. As Clay Shirky (2008) put it, some forty-six years later, “any radical change in our ability to communicate with one another changes society” (p. 106). Engelbart could see that these changes could bring unprecedented benefit, but he also knew that computing could fall far short of its potential benefit or even become quite harmful. Engelbart understood that our ingenuity could become a trap baited with clever tricks, a situation in which, having been shaped by our tools, we lost our power to shape those tools.

For the arts of inquiry do not proceed along linear trajectories. They do not lend themselves to algorithmic formulation. The arts of inquiry rely on the human ability to think abstractly and by analogy—analogy being, as Douglas Hofstadter (2001) insists, the core of cognition (p. 499–500). The arts of inquiry must be elicited, suggested, modelled, encouraged, not mapped or outlined or simply “transmitted.” They are stimulated, for example, by exercises such as Brian Eno’s and Peter Schmidt’s “Oblique strategies: Over one hundred worthwhile dilemmas” (1975), a set of cards in which each card conveys an instruction that by design is *not* directly related to the task at hand. Yet these instructions are not irrelevancies, but wise advice emerging from the creative experiences of Eno and Schmidt themselves:

These cards evolved from separate observations of the principles underlying what we were doing. Sometimes they were recognized in retrospect (intellect catching up with intuition), sometimes they were identified as they were happening, sometimes they were formulated.

They can be used as a pack (a set of possibilities being continuously reviewed in the mind) or by drawing a single card from the shuffled pack when a dilemma occurs in a working situation. In this case the card is trusted even if its appropriateness is quite unclear. They are not final, as new ideas will present themselves, and others will become self-evident.

Such oblique strategies strongly resemble what Doug Engelbart (2003) wrote forty years after *Augmenting Human Intellect* as he considered the uniquely important goal of not simply improving a process but “improving our ability to improve,” an activity he termed a “C-level” activity, where “A” is the initial process or goal and “B” is the process of improving “A.” Engelbart recognized that without that “C” level, humankind cannot “bootstrap” itself into new ways of thinking, but will be chained to the endless task of refining current practices instead of reinventing them in a true advance.

At the C level we are trying to understand how improvement really happens, so that we can improve our ability to improve. This means having different groups exploring different paths to the same goal. As they explore, they constantly exchange information about what they are learning. The goal is to maximise [sic] overall progress by exchanging important information as the different groups proceed. What this means, in practice, is that the dialog between the people working toward pursuit of the goal is often just as important as the end result of the research. Often, it is what the team learns in the course of the exploration that ultimately opens up breakthrough results. (p. 162)

To what extent does the culture of AI stimulate exploration, and to what extent does it substitute spoon-feeding for exploration even as it conceals that substitution behind an apparently information-rich and confidently authoritative “voice”?

Engelbart (2003) goes on:

[A]t the C level ... [w]e are not trying to solve a specific problem, but ... reaching for insight into a broad class of activities and opportunities for improvement.... I have routinely found that when I seem to reach a dead end in my pursuit of a problem, the key is usually to move up a level of abstraction, to look at the more general case.... [T]his is directly counter to the typical approach to solving focused, B-level problems, where you typically keep narrowing the problem in order to make it more tractable. In our work on improving improvement, the breakthroughs come from the other direction—from taking on an even bigger problem. (p. 162–163)

I can imagine forms of AI prompting its users to move up a level of abstraction, to adopt oblique strategies. Yet this would mean reimagining our relationship not only to AI, but to learning itself, especially within the culture of education. My fear is that AI, of whatever variety,

will seduce us into focusing only on the tractable, and exclude the very notion of wicked problems or open-ended searching. Our ability to get to what Engelbart terms the “C-level,” another name for the arts of inquiry, will weaken and die.

Inquiry and Wisdom

The phrase “arts of inquiry” may seem too abstract in the current heated conversation about practical benefits conferred by generative and agentic AI, so let’s consider two specific risks: the diminishment of insight and the diminishment of wisdom. In contrast to knowledge, insight results from new neural connections, an “a-ha!” experience familiar to teachers and learners and a neuropsychological phenomenon that can be measured by EEGs (Kandel, 2012). Eric Kandel describes psychologist Jonathan Schooler’s conclusions in this regard:

All of a sudden, ideas that were previously isolated come together and people see connections that had escaped them—and others—before.... [P]roblems requiring creative insight are very likely to lead to an impasse—a state in which the person does not know what steps to take next; and ... such problems are quite likely to lead to a sustained effort that is rewarded with a sudden insight that breaks the impasse and clearly reveals the solution. This situation is thought to arise when the problem solver breaks free of unwarranted assumptions and forms novel, task-related connections between existing concepts or skills. (p. 458)

Kandel concludes that “[a]lthough problem solving generally relies on shared cortical networks, the sudden flash of insight that occurs when we engage distinct neuronal and cognitive processes seems to allow us to see connections that had previously been elusive” (p. 482).

What becomes of the potential for such connections—such insights—when learners rely on Gen AI to write their papers for them? A study by MIT researchers (Kosmyna et al., 2025), not yet peer-reviewed at the time of this writing but available as a preprint from arXiv.org, found that using ChatGPT to write an essay substantially reduced intraneural connectivity, as well as diminishing the ability to feel “ownership” of one’s work and quote from it reliably and extensively. Moreover, the disposition of students using genAI extensively and indiscriminately is chillingly demonstrated by a *New Yorker* article featuring “Alex” (a pseudonym), a student at New York University who laughingly admits to the truth about the two genAI-written essays he had turned in during finals: “I didn’t retain anything.... I couldn’t tell you the thesis for either paper hahahaha” (Hsu, 2025).

This is not to say that no legitimate, cognition-strengthening uses of generative and agentic AI exist. The *New Yorker* article cited above points out some of them, and every day the news from the sciences suggests both startling potential and realized advances in laboratory analysis, medical diagnosis, and other essential areas. Nevertheless, the MIT study (Kosmyna et al., 2025) sounds a clear and urgent warning we do well to heed: “in this study we demonstrate the pressing matter of a likely decrease in learning skills.... The use of LLM[s] had a measurable impact on participants, and while the benefits were initially apparent, as we demonstrated over the course of 4 months, the LLM group’s participants performed worse than their counterparts in the Brain-only group at all levels...” (p. 2). The researchers conclude that “longitudinal studies

are needed in order to understand the long-term impact of the LLMs on the human brain, before LLMs are recognized as something that is net positive for the humans” (p. 143).

And what of wisdom, which one might call the accumulation of insight across a lifetime? Here we might turn to the research on wisdom undertaken by investigators across disciplines and at centers ranging from the Center for Lifespan Psychology at the Max Planck Institute for Human Development (<https://www.mpib-berlin.mpg.de/research/research-centers/lifespan-psychology>) to the Center for Practical Wisdom at the University of Chicago (<https://wisdomcenter.uchicago.edu/>). One influential theory of wisdom, the Berlin Wisdom Paradigm, connects knowledge to wisdom with the concept of “wisdom-related knowledge” assessed on the basis of “rich factual knowledge, rich procedural knowledge, life-span contextualism, value relativism, and uncertainty” (Steinberg and Jordan, 2005, p. xiii). Even a more cautious approach toward assessing wisdom, such as seen in “Can we measure practical wisdom?” (Swartwood, 2020), concludes that the goal is worthwhile and requires an essentially interdisciplinary approach:

Philosophical reasoning can help us specify which practical wisdom-relevant characteristics (e.g., reasoning or discrimination skills or processes, self-regulation skills or habits) are logically entailed by a rationally defensible account (such as the minimal philosophical conception). Empirical research can then determine how these can be developed and how they relate to other characteristics whose necessity for practical wisdom is more contentious or contingent on facts about human psychology. (For example, does an ability to give advice or justify one’s choices tend to develop as a result of acquiring the reasoning and self-regulation processes that are part of a philosophically plausible picture of wisdom?) Even if the results of such an investigation would not be sufficient to allow us to measure practical wisdom or its components, they still would provide valuable information about some of the necessary conditions for having or developing practical wisdom and a general picture of some of the ways it would be likely to manifest in real human lives. (Compare general best practice measures of teaching: they can help us acquire a fuller picture of good teaching and how we can improve, even if they do not constitute measures of teaching expertise and should not be used as such.) (p. 91)

How might generative or agentic AI serve to develop and strengthen those essential elements of wisdom? It would be foolish (the opposite of wise) to argue such benefits are impossible. Yet it is fair to say that the multi-billion-dollar gold-rush mentality on display at the leading platforms for AI research—Google, Meta, Claude, OpenAI, etc.—does not suggest a thoughtful and usefully cautious approach to this question. Instead, as prior sections of this very article make clear, the potential damage wrought by indiscriminate uses of generative and agentic AI may pose existential threats to human culture and civilization: in short, a dark age, defined by Jane Jacobs (2004) as a time when even the memory of a more enlightened age disappears.

Indeed, in her final book, *Dark Age Ahead*, Jacobs describes a culture of education badly in need of reform:

All universities possess their own subcultures, and so do departments within universities, varying to the point of being indifferent or even antagonistic to one another, so a generalization cannot describe all accurately. But it is safe to say that credentialing as [the] primary business of institutions of higher learning had gotten under way in the 1960s. Students were the first to notice the change. In the unrest and turbulence of that decade, one thread of complaint came from students who claimed they were shortchanged in education. They had expected more personal rapport with teachers who had become only remote figures in large, impersonal lecture halls. The students were protesting attempts to transmit culture that omitted acquaintance with personal examples and failed to place them on speaking terms with wisdom. In another decade, however, students dropped that cause, apparently taking it for granted that credentialing is the normal primary business of institutions of higher learning and that its cost is an unavoidable initiation fee into acceptable adulthood. (p. 46–47)

The goal of being on “speaking terms with wisdom,” always ambitious, may recede forever out of reach without a much more thoughtful and discriminating exploration of AI. If personal rapport with teachers and other experiences of the arts of inquiry become mere “prompt engineering,” what becomes of insight and wisdom? When teaching assistants are agentic AI bots, a program the University of Michigan and Google are already implementing (“Google Public Sector,” 2025), when premium genAI corporations offer their products for free to students, with a wink, saying “Good luck with finals!” (Shroff, 2025), lifelong learning degenerates into brand loyalty and individual agency becomes an illusion. Higher learning partnering with a global data-hoovering behemoth of unparalleled wealth and influence. Students having the very best cheating resources freely available at a critical moment in strengthening and assessing their learning. What could go wrong? The profit from learning used to be metaphorical and applied to the learners themselves. Now the profits accrue to the corporations as non-profits brag about student success and for-profits brag about market penetration and shareholder returns. Do such strategies nurture the arts of inquiry, foster insight, or inculcate wisdom? Do they reveal a commitment to nurturing “creative, curious, caring, and collaborative learners,” the “4C” approach advocated by MIT Media Lab Professor of Learning Research Mitchel Resnick (2025)? I am skeptical.

It need not be this way. Perhaps there is still time to pursue the arts of inquiry in the culture of education. The beneficial potential of AI can be realized only in such a pursuit. Perhaps we can rediscover and renew our commitment to the idea of school as what Bruner calls “an exercise in consciousness-raising about the possibilities of communal mental activity” and not simply a transactional environment narrowly imagined as “a means for acquiring knowledge and skill” (*Culture of Education*, 1996). Indeed, we must. The alternative is dire: a self-satisfied, AI-generated somnambulism from which we may never awaken.

Finally: A Way Forward

The concept and functionality of artificial intelligence struggled for decades because of computational limitations, data scarcity, misunderstanding intelligence, and reliance on symbolic approaches. This led to multiple cycles of overpromising and underdelivering. However, in recent years advances in deep learning, big data coupled with computational sophistication, and hardware make it clear that artificial intelligence, digital education, information availability, organizational onboarding, human thinking and creativity, quality, and the roles of teachers and

students will be impacted. AI has resulted in positive outcomes. In medicine, more effective diagnostic and treatment procedures are being developed daily. Self-driving vehicles and traffic management are reframing transportation. Newly developed assistive AI technologies are improving the lives of people with disabilities. Accelerated data and text analysis, predictive modeling, and simulation techniques are accelerating scientific research. Cybersecurity has increased. Real-time language translation is creating effective communication patterns. In education, curriculum development is progressing. Teachers are being relieved of time consuming non-instructional tasks. Professional development is improving. Coaching and mentoring services powered by AI increase students' learning effectiveness. AI has taken adaptive learning to a whole new level of effectiveness. Big data analytics and pattern recognition have accomplished information processing results heretofore thought impossible. Learning environments are being optimized by intelligent management systems. The opportunities for diverse learners have increased. These comprise a small sample of how artificial intelligence can improve the human condition. However, as we attempt to frame the context of how AI should be considered it is important not to become binary in our thinking—as in AI is good or bad. The question is more nuanced. We must build the proper reference contexts so that we can better understand the long-term impacts of modern technologies that can create things and ideas, make decisions, and function as autonomous agents that we may not be able to control.

The potential for humankind is limitless but the ways forward are impossible to understand at present. The rapidity with which this is happening surpasses most everything we have experienced in the past. However, there are consequences on the horizon and the future is uncertain at best. By what baselines are we to judge these developments? What if we have entered an era of hyper history where information communication technologies including artificial intelligence communicate only with each other, leaving humans out of the loop? What are the implications for transcending their training and creating, conceptualizing, and communicating in a nuanced and symbolic manner that we may not understand? This may seem like science fiction, but it is a possibility. As mentioned in this article, it is impossible to sense how these developments will impact our lives, and clearly, we will be challenged by unanticipated side effects. As a result, we find ourselves caught up in a web of ambivalence: enthusiastic anticipation and simultaneous concern and foreboding. So many possibilities for enabling humankind are on the horizon. For instance, consider the potential for learning. The fundamental components of contemporary learning theory are:

1. Behaviorism focuses on observable behavior shaped by instructional environments where behavior change indexes learning.
2. Cognitivism emphasizes mental processes such as memory, attention, and problem solving where knowledge acquisition reflects learning.
3. Constructionism where students formulate their unique understanding through experience and interaction.
4. Connectivism depends on the digital network where learning resides in a network structure.

We can hypothesize that artificial intelligence will reframe those learning components into an enhanced and more comprehensive theory. For example, knowledge might be viewed as a

dynamic network based on emergent curricula. The instructor might gravitate further to the facilitator and ethical counselor role. The learner will abandon the remnants of passive learning, reconfigure cognitively, and become more self-directed while maintaining human analytic capabilities. The learning environment will embrace ambient intelligence, simulation, and coalesced formal and informal learning. A reasonable assumption is that artificial and human intelligence will interact in a yet unknown complex system where the learning theory of the future will depend more on the elements' interactions instead of their definitions. The long-term and unanswered question is, however, will a meaningful balance between human and artificial learning result?

One of the fundamental problems in AI is alignment, that is, ethical guidelines and guardrails for AI that help ensure humane outcomes in support of human flourishing. Ironically, alignment depends on just the kinds of learning in practical wisdom that widespread use of AI in education, by both students and teachers, may erode or irreparably damage. In an interview on the podcast *The Good Fight with Yascha Mounk*, technical advisor Dean Ball describes the nature and importance of the alignment problem: "People should not dismiss the notion of alignment. It is a real thing. But they assume that it is a problem susceptible to a solution, like one magic solution, like an equation that can be solved and is one hundred percent solved at that point. We do not think alignment is that. We think alignment is much more of what we would describe as a muddle-through problem. Alignment is much closer to the articulation of philosophy.... [I]f the alignment problem were susceptible to a one hundred percent solution, that would be equivalent to solving philosophy.... {But if} doing philosophy well is an important part of alignment, then that is something we know how to do. We are not perfect at it, but it is not something you can ever perfect. We have practice, experience, and a deep body of knowledge to draw on.... Perhaps we are being too optimistic. We do not want to leave the impression that the work is done or that this model [Anthropic's "Soul Document"] solves alignment. It does not...." (Mounk, 2026).

But alternatively, threats to integrity and our value systems loom on that same horizon. AI systems are becoming increasingly opaque and less transparent. Mathematically complex components such as tokens defy direct understanding and become the object of awkward metaphors. Knowledge acquisition becomes a series of perturbations with these systems. Therefore, we leave the readers with a series of long-term questions for their consideration.

1. How can educational systems be designed to maximize AI's potential for enhancing cognitive skills while strengthening analogous abstract and nuanced problem solving?
2. How will educators and students accommodate an increasingly autodidactic educational environment?
3. How can we ensure recency of AI-generated information for critical applications like education when these platforms are frozen at their time of training?
4. How can we ensure that AI-driven personal benefits exist for learners while excluding existing inequalities in training data?
5. What is the emerging paradigm of authorship, authority, and intellectual property?
6. Considering the power law distribution of information sources, how will we develop information fluency skills in students and what role will educators play in the process?

7. How can we incorporate AI systems and educational theories and practices that promote active learning and authentic understanding rather than passive acquisition of information—is AI unraveling academia?
8. Is it possible for AI to become a partner rather than a dominance in the inquiry process, and if so, how will this change the pursuit of knowledge?
9. How can we foster genuine interdisciplinary collaboration, learning, and research in the transformed AI educational environment?
10. What integrity-review-and assessment processes will educators develop and adopt to screen out “bad actor” AI made possible by open source frontier AI, particularly when bad-actor interventions (one might say, “hacking”) in training and alignment can have catastrophic results for learners’ lives?
11. How can curricula re-emphasize core learning in the humanities, especially ethics and moral philosophy, to help students judge the character and merits of AI systems and reliably infer the alignments those systems have undergone?
12. How can we marshal a collective and thoughtful response to unavoidable and unanticipated side effects in large language models that produce inappropriate or harmful outcomes, such as the sycophancy problem, where AI disproportionately generates positive and validating responses to users regardless of their prompt accuracy or appropriateness?

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There are no supplementary materials for this manuscript except for those provided by the references

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Understanding the Generative AI Divide: Faculty and Student Perspectives in Higher Education

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Abstract

As generative artificial intelligence (GenAI) tools rapidly transform educational landscapes, higher education institutions face the critical challenge of developing effective policies and guidelines for their integration. However, little empirical research has examined actual GenAI usage patterns, perceptions, knowledge assessments, and training needs among faculty and students in U.S. universities. This study presents findings from a comprehensive survey of 3,164 students and 166 faculty members at a large R1 university in the southeastern United States. Results indicate that while 88% of students are familiar with GenAI concepts, only about a quarter currently use these tools for academic work, and 76% have received no formal classroom instruction on their use. Faculty demonstrate comparable familiarity (mean 4.5/5.0) but report substantial support needs, with 65% requesting assistance in creating AI-resistant assessments and 63% seeking guidance on effective GenAI integration in teaching. Before universities can implement effective GenAI guidelines and policies, they must first understand the current landscape of usage, perceptions, and training needs among their academic communities.

Keywords: Generative AI, GenAI, higher education, faculty development, student learning, educational policy, artificial intelligence

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The rapid emergence of generative artificial intelligence (GenAI) technologies has created unprecedented challenges and opportunities within higher education. No prior technology has moved with the speed with which artificial intelligence (AI) platforms are progressing. Chat-based tools such as ChatGPT, Claude, Gemini, and other large language models (LLM) are poised to fundamentally alter how students approach learning tasks and how faculty conceptualize teaching and assessment (“7 Things You Should Know About Generative AI,” 2023; Basgen, 2023). Yet despite the transformative potential of these technologies, to date, little empirical research has been conducted to understand how GenAI is being used within U.S. universities, and how faculty and student perceptions and use differ. Calls for more information and guidance is prevalent among those in higher education (Swindell et al., 2024; Tyton Partners, 2024; Brennan et al., 2025).

This study reports on an ongoing research project that is tracking faculty and student reactions to and uses of GenAI in teaching and learning at the University of Central Florida (UCF). UCF is the largest university in the Florida State University System with 70,674 students as of Fall 2025. UCF is classified as an R1 school with 250 degree programs and 13 colleges. The student body is diverse with 58.7% minority students and an average student age of 23.3. UCF has a strong technology focus with nearly 60% of student credit hours being in online and blended courses. Ninety-one percent of all UCF students take at least one online or blended course and 86% of UCF students take at least one fully online course. As a school that began as Florida Technological University, and often recognized as one of the top 10 in innovation among public universities (<https://www.ucf.edu/>), both students and faculty are well-versed in using the latest technologies.

UCF’s Artificial Intelligence for All initiative guides the campus in teaching and learning with AI (<https://aiforall.ucf.edu/>). The university provides Microsoft CoPilot to all students and employees as a protected “walled-garden,” allowing them to use GenAI in a controlled, closed system. In addition, both the Faculty Center for Teaching and Learning, and the Center for Distributed Learning provide courses related to GenAI use for faculty and students. Verbiage and guidance for course syllabi are provided with suggestions on how to address both GenAI use by students and GenAI use by faculty. Ongoing instruction and conversations are also regularly occurring to identify issues and address faculty concerns with regards to GenAI.

In Fall 2024, the Division of Digital Learning’s Research Initiative for Teaching Effectiveness began pilot surveys of both faculty and students to capture GenAI use of AI on campus. In this paper we report on our Spring 2025 surveys of faculty and students illustrating the most reported attitudes and uses of this revolutionary technology in teaching and learning on our campus.

Literature Review

As generative AI (GenAI) tools become increasingly embedded in academic life, understanding how students and faculty are using and perceiving them has become a pressing priority for higher education. Yet despite the growing volume of scholarship on this topic, significant gaps remain in what is known, particularly regarding how student and faculty perspectives compare, and whether findings from discipline-specific or single-institution studies

reflect broader patterns across American higher education. This literature review synthesizes studies published between June 2025 and February 2026 to examine what the current evidence base reveals about GenAI use and perceptions at American colleges and universities.

How Students Are Using Generative AI

How students are using GenAI in their academic work is among the most pressing yet underexplored questions facing higher education today, and only seven of the 24 studies reviewed provided direct insight into these patterns. Across these studies, the two most commonly reported uses of GenAI were writing support and understanding content. Four of the seven studies identified writing support as a primary use. Golding et al. (2025) found that writing was the most common task for which students used generative AI in college (32%), with use most concentrated in humanities courses; related tasks such as generating ideas and starting essays also emerged as common uses in the study's qualitative analysis. Similarly, Onal et al. (2025) found that across disciplines, students commonly used ChatGPT for academic writing support tasks such as brainstorming, outlining, editing, and paraphrasing. Maxwell et al. (2025), drawing on a sample of 460 students across institutions in 41 states, reported that writing technical documents was among the top academic uses (38%), and Hazari (2025) found that marketing students planned to use ChatGPT primarily for writing, research, and brainstorming.

Using GenAI to support learning and content understanding was identified in four of the seven studies as well. Onal et al. (2025) found students often turned to ChatGPT as a supplemental resource when instructor access was limited, Maxwell et al. (2025) reported that asking general knowledge questions was the most common academic use (52.2%), Divekar et al. (2025) noted that students most frequently used ChatGPT to create and understand academic content, and Wilson et al. (2025) found that students described one of their primary uses as “kinda like a tutor” for academic support. While these findings span a range of institutional contexts and disciplines, they consistently point to writing support and learning support as among the most common academic functions students report for GenAI tools, though additional research across a broader range of populations will be needed to determine how generalizable these patterns are.

A recurring tension across the studies is the gap between students' reported use of GenAI and their own ethical assessments of that use. Golding et al. (2025) found that 56% of students perceived using generative AI as a form of academic cheating, yet 8% admitted to using it anyway—a pattern Stone (2025) further illuminated by finding that 41% of students had used AI in explicitly banned ways and 59% in ambiguous circumstances. Stone (2025) also found that students who overestimated how many peers were cheating with AI were more likely to engage in that behavior themselves, pointing to a social norming dynamic that may accelerate non-sanctioned use. Hazari (2025) found that while 75% of marketing students believed ChatGPT should be allowed in courses, academic dishonesty and technology dependence were their top perceived drawbacks. Maxwell et al. (2025) reported that students' ethical awareness scores were moderate ($M = 3.72/5$), suggesting that students had a foundational but not robust understanding of the ethical dimensions of GenAI use. Compounding this, Slepchuk and John (2025) found that conflicting policies across university, course, and instructor levels created inconsistency in how students understood and navigated guidelines around AI use. Stone (2025) further found that students whose professors actively integrated GenAI into their courses reported higher usage

across all categories, including banned use, suggesting that faculty instructional choices directly influence student behavior regardless of institutional policy. These findings suggest that student use of GenAI is shaped, at least in part, by perceptions of peer behavior, the consistency of institutional and course-level policies, and the degree to which faculty actively integrate GenAI into their teaching—factors that policy developers may need to consider alongside questions of access and AI literacy.

Student and Faculty Perceptions of GenAI

Across the studies reviewed, perceptions of GenAI in higher education reflect a complex and uneven landscape: students tend to approach these tools with cautious optimism, while faculty attitudes range from guarded acceptance to outright negativity, with concerns about academic integrity, overreliance, and critical thinking running consistently through both groups. Maxwell et al. (2025) found that the majority of students felt comfortable using GenAI and recognized its potential to enhance productivity and academic success, yet also reported meaningful concerns about ethics, privacy, and negative educational impact. Hazari (2025) described students as expressing “guarded enthusiasm,” acknowledging ChatGPT’s academic utility while identifying academic dishonesty, technology dependence, and information inaccuracy as significant drawbacks. Wilson et al. (2025) captured this duality through students’ own metaphor, describing AI as “like a knife”—a tool with both beneficial and harmful potential depending on how it is wielded. Walker et al. (2026) further corroborated this pattern, finding that perceived utility was a significant predictor of GenAI use frequency among social work students, and that AI knowledge was a second independent predictor, explaining 21.4% of the variance in use frequency. These findings suggest that both students’ recognition of GenAI’s practical value and their familiarity with the technology meaningfully drive adoption. From the faculty perspective, Malik et al. (2025) found that academicians across three continents viewed ChatGPT favorably for its ability to enhance productivity, support personalized instruction, and support research activities, but raised parallel concerns that GenAI use in research could diminish writing quality through reduced practice and “text dumping,” stifle critical thinking and originality, and promote only a superficial understanding of research topics and methodologies. Blomquist et al. (2025), studying nursing students and faculty at a single U.S. institution, found that both groups held similarly moderate levels of confidence and perceived helpfulness regarding GenAI, though faculty rated its importance for future careers significantly higher than students did, most likely due to faculty’s broader professional vantage point. Taken together, these findings suggest that both students and faculty are grappling with the same fundamental tension: GenAI offers genuine utility, but its unrestricted use may come at a cost to deeper learning.

Important differences emerge between how students and faculty perceive the scale and frequency of student GenAI use, with faculty consistently overestimating student engagement. Saeli et al. (2026) found that instructors overestimated student GenAI use on 84% of parallel survey items, with the largest gap on overall frequency of use, where students reported a mean of 1.83 on a 6-point scale compared to instructors’ estimate of 3.19. Instructors also overestimated students’ trust in GenAI feedback and students’ preference for GenAI over human sources of help such as tutors, writing instructors, and peers. Slepchuk and John (2025) similarly found that marketing educators overestimated their students’ current AI use, even as both groups agreed that use would increase substantially in the future. Kim et al. (2025) found that while students and

faculty held similar behavioral intentions toward GenAI and comparable usage rates, with approximately 70% of both groups using GenAI tools less than once per week, students found GenAI easier to use and more enjoyable, while faculty who did use it had incorporated it more routinely into their workflow. Angehr and colleagues (2026), in a study of more than 3,000 faculty, reported that 77% had used GenAI in their professional role, yet 47% of those users reported using it for only one or two purposes, and 45% held negative overall sentiment toward GenAI in higher education, with non-users particularly more negative (69%). These figures suggest that low faculty engagement with GenAI may reflect resistance as much as inexperience, a distinction with implications for how professional development efforts are designed. Students were also significantly more optimistic than faculty about GenAI's potential to improve academic performance, though both groups tended to view it as having more negative than positive effects on learning competencies such as critical thinking, problem-solving, and intrinsic motivation. These findings suggest that faculty assumptions about student behavior may not be well-calibrated, which has direct implications for how policies and course-level guidelines are designed.

The studies paint a complicated picture of how students perceive GenAI in relation to academic integrity, with stated values not always matching reported behavior. Lund et al. (2025) found that 96% of students were aware of their institution's academic integrity policies, and 84% viewed using ChatGPT to write an entire paper as a major form of misconduct—a level of severity comparable to copying from another student. However, students drew meaningful distinctions based on scale, with only 51% viewing AI-generated paragraphs as major misconduct and 60% not viewing grammar and spell-checking tools such as Grammarly as misconduct at all. Stone (2025) extended this picture by revealing that actual student behavior does not always align with these stated values: 41% of students reported using AI in explicitly banned ways, and 59% had used it in ambiguous circumstances. Students also tended to overestimate how much their peers were cheating with AI, and this overestimation, along with general AI familiarity and excitement, predicted their own cheating behavior. Among nursing students, Blomquist and colleagues (2025) found that 73% of students reported concern about academic misconduct accusations as the primary barrier to student AI adoption. This finding suggests that integrity anxieties not only shape how students think about GenAI but whether they use it at all. Kim et al. (2025) found that approximately 80% of both students and faculty agreed that GenAI should not be banned outright and that universities should develop formal policies.

Faculty adoption of GenAI appears to be shaped less by technical confidence than by trust and institutional culture. Shata and Hartley (2025), in a study of social sciences and humanities faculty at two U.S. universities, found that perceived usefulness was a far stronger predictor of GenAI adoption than perceived ease of use, and that trust emerged as the single most significant predictor across all adoption-related constructs. Social reinforcement—the extent to which colleagues and professional networks normalize GenAI use—also significantly predicted faculty attitudes and behavioral intentions, suggesting that institutional culture plays an important role in whether faculty engage with these tools at all. Malik et al. (2025) reinforced this point, with faculty participants emphasizing that effective ChatGPT integration in teaching requires training and that traditional pedagogical approaches would need to evolve. The importance of clear institutional communication was further illustrated by Blomquist et al. (2025), who found that although 77% of nursing faculty addressed AI use in their courses, one-

third of students remained uncertain about what uses were permitted and 15% believed AI was universally prohibited, a policy communication gap suggesting that even well-intentioned faculty messaging falls short without formalized institutional policies. Students in Wilson et al. (2025) perceived faculty as polarized in their opinions of AI and called for both faculty development and more nuanced institutional policies in lieu of blanket prohibitions. Across these studies, perceptions of GenAI are not fixed but are actively shaped by faculty and institutional messaging, peer influence, and the extent to which both students and faculty are supported in navigating this technology.

Methodology

Survey development began with a comprehensive literature review to identify key constructs related to GenAI usage, familiarity, and perceptions that were reported across higher education institutions. This provided a foundation which was tailored for our college faculty and student populations, with questions gauging their familiarity with GenAI concepts, tools, and functions; understanding of GenAI limitations; ethical considerations and academic integrity; current usage patterns in academic work; perceptions of GenAI's impact on learning; and perceived training and support needs.

The research was conducted in two phases. In Fall 2024, pilot questionnaires were administered to 677 students and 79 faculty members. Surveys were administered to students and faculty via the Instructure Canvas main landing page (dashboard) with timing occurring after spring break and midterms to avoid conflicting priorities. This also gave students and faculty enough experience with the semester courses to both have experience with GenAI and have formed opinions regarding its use in instruction. Faculty are required to use the Canvas gradebook, irrespective of course modality, so students and faculty frequent the platform and are comfortable with this method of receiving campus-wide announcements. Following data collection, the questionnaires underwent iterative review and revision, informed by findings from the pilot study. This refinement process ensured that items were clear, relevant, and appropriate for the target populations and that we were able to incorporate any campus or GenAI updates into questions. The refined questionnaires were then deployed in Spring 2025, with 3,164 students and 166 faculty members responding.

Participants

Students

The student sample ($n = 3,164$) provided a range of student demographic perspectives, with 63% enrolled full-time, 58% upper-level undergraduates, 54% first time-in-college, 31% first-generation, and 34% Pell-eligible. The university has 13 colleges, and the top three colleges represented were Sciences (30%), Engineering and Computer Science (26%), and Arts and Humanities (17%).

Faculty

The faculty sample ($n = 166$) had an average age of 49 years and 17 years of teaching experience. Seventy-eight percent (78%) had taught online or blended courses in the past academic year, and 72% primarily taught undergraduate students. Faculty ranks included Professors (36%), Instructors (22%), Lecturers (21%), and Adjuncts (15%), with the top colleges

represented being Arts & Humanities (27%), Community Innovation & Education (26%), and Sciences (18%).

Results

Familiarity and Understanding of GenAI

As seen in Table 1, both students and faculty demonstrated high levels of familiarity with GenAI concepts, though significant differences emerged in comfort and application. On a Likert scale of *strongly agree* (5) to *strongly disagree* (1), students reported strong familiarity with GenAI concepts ($M = 4.3$, $SD = 1.0$) and awareness of different tools and functions ($M = 4.2$, $SD = 1.0$). Faculty showed slightly higher familiarity ($M = 4.5$, $SD = 0.7$) and comparable awareness ($M = 4.2$, $SD = 0.8$).

Faculty and students both reported less comfort with using GenAI. However, comfort levels revealed important disparities between faculty and students. Faculty reported significantly higher comfort using GenAI tools ($M = 3.7$, $SD = 1.2$) compared to students ($M = 3.2$, $SD = 1.4$, $p < .001$). Interestingly, students found learning GenAI tools significantly simpler ($M = 3.7$, $SD = 1.0$) than faculty ($M = 3.4$, $SD = 1.0$, $p < .001$), which may be reflective of students' overall comfort with technology or flexibility to learn new skills. Both groups reported generally lower ratings with questions that implied more knowledge or use of GenAI.

Table 1

Familiarity with GenAI Tools & Functions (Student $n = 3,144$; Faculty $n = 167$)

Familiarity	Student		Faculty	
	Mean	Standard Deviation	Mean	Standard Deviation
Familiar with the concept of GenAI**	4.3	1.0	4.5	0.7
Aware of different GenAI tools, technology, and functions	4.2	1.0	4.2	0.8
Learning how to use GenAI tools is simple**	3.7	1.0	3.4	1.0
I know the limitations of GenAI	3.7	1.2	3.9	1.1
Comfortable using GenAI tools**	3.2	1.4	3.7	1.2
I can think of new uses for GenAI**	3.2	1.2	3.6	1.1

** $p < .001$

Both groups showed moderate understanding of GenAI limitations (Table 2), with faculty demonstrating better perceived recognition of privacy and security concerns ($M = 4.3$, $SD = 0.8$) compared to students ($M = 4.0$, $SD = 1.1$, $p < .001$). Faculty showed greater perceived awareness of the difficulty in detecting AI-generated content, both for written work ($M = 3.3$, $SD = 1.0$) and visual content ($M = 3.1$, $SD = 1.0$), compared to students ($M = 2.9$, $SD = 1.1$; $M = 2.4$, $SD = 1.2$, respectively, $p < .001$); although both students and faculty had lower confidence in their ability detecting this content.

Table 2*Understanding of GenAI Limitations (Student n = 3,144; Faculty n = 167)*

	Student		Faculty	
	Mean	Standard Deviation	Mean	Standard Deviation
GenAI has limitations in its ability to handle complex tasks	4.1	0.9	4.1	0.8
GenAI systems raise privacy and data security concerns**	4.0	1.1	4.3	0.8
GenAI systems can perpetuate bias or discrimination*	3.8	1.1	4.1	1.0
GenAI systems consistently produce factually accurate output	3.6	1.1	3.7	1.0
GenAI consistently gives same output with same prompt**	3.4	1.1	3.8	1.1
It can be difficult to tell if written content was created by AI**	2.9	1.1	3.3	1.0
It can be difficult to tell if art/image content was created by AI**	2.4	1.2	3.1	1.0

* $p < .01$; ** $p < .001$ ***Current Usage Patterns***

Perhaps the most striking finding was that 48% of students indicated that they are not currently using GenAI for academic work, despite high levels of familiarity with the technology. Similar low usage patterns were reported by Kim and colleagues (2025). Among students reporting not using GenAI in their academics (Table 3), the most reported (very often/often) applications were: assisting with studying (26%), brainstorming ideas (26%), editing papers and essays (26%), and completing course assignments (26%). Less frequent uses included summarizing information (21%), researching topics (21%), and writing papers and essays (21%).

Students who reported that they do not use GenAI for academic work were distributed across colleges, with the highest concentrations in Sciences (22%), Arts & Humanities (16%), and Engineering and Computer Science (10%). Among all students, 88% were familiar with GenAI. Notably, among non-users, 83% indicated that they were familiar with GenAI concepts and 80% were aware of different tools and functions, but only 22% reported being comfortable using GenAI tools.

Table 3*Students' Self-Reported Use of GenAI in Academic Work*

AI Uses	<i>n</i>	Very Often/ Often	Sometimes/ Rarely	Never
Assisting with studying	2,818	26%	23%	52%
Brainstorming ideas	2,810	26%	27%	47%
Editing papers/essays	2,813	26%	27%	47%
Completing course assignments	2,806	26%	23%	52%
Summarizing information	2,808	21%	26%	53%
Researching topics	2,813	21%	24%	52%
Writing papers/essays	2,817	21%	24%	52%

Among students who use GenAI academically, the primary reported motivations for doing so were working more efficiently (42%), improving work quality (41%), and developing academic skills (37%). This suggests that students may view GenAI primarily as a productivity and enhancement tool rather than a replacement for their own thinking.

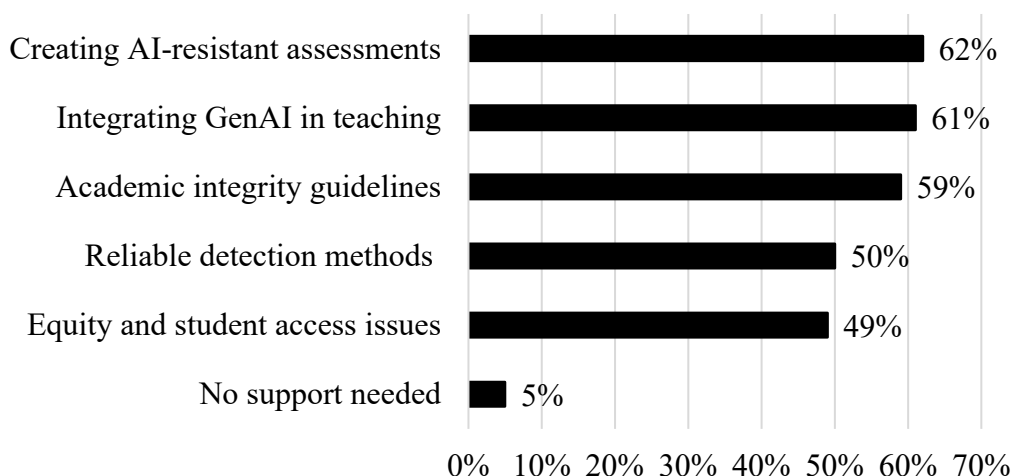
Faculty Implementation and Support Needs

Faculty implementation of GenAI in their courses showed considerable variation. Only 33% of responding faculty reported encouraging students to explore GenAI tools in all their courses, while 48% of students reported never being encouraged to explore these tools. Similarly, only 18% of faculty taught students how to use GenAI tools in all their courses, while 76% of students reported never receiving such instruction.

A highly addressed topic was GenAI ethics. While 40% of faculty reported discussing GenAI ethics in all their courses, 43% of students reported never encountering the topic, suggesting that coverage remains inconsistent and that a substantial portion of students are not being reached.

Faculty reasons for not encouraging or teaching GenAI cited several key barriers: faculty lack of comfort with the technology (42%), opposition to student use (41%), cheating concerns (39%), and the belief that foundational skills should be developed before using AI (36%). Time constraints (25%) and perceived lack of value (18%) were less reported factors.

Faculty support needs for GenAI training and guidance were both substantial and specific, as illustrated in Figure 1. Only 5% of faculty indicated they needed no additional support—meaning the vast majority identified at least one area where they wanted guidance. The most commonly requested training needs were creating AI-resistant assessments that require original student thinking (62%); effective methods for incorporating GenAI into their teaching (61%); academic integrity guidelines, including policies for appropriate student use and attribution of AI-generated content (59%); reliable methods for detecting student cheating (50%); and addressing equity and access concerns related to GenAI use in the classroom (49%).

Figure 1*Top Areas Faculty Request Additional Supports****Policy and Guidelines***

Faculty course policies regarding GenAI showed considerable variation and uncertainty. The most common approach was requiring citation/documentation for GenAI use (34%), followed by having no formal policy (29%). Twenty-four percent (24%) prohibited GenAI entirely, while only 4% allowed its free use.

Students strongly supported transparent communication from faculty about GenAI policies, with 75% believing course syllabi should include both guidelines on acceptable student use and information on how professors might utilize GenAI. This alignment between faculty communication methods (65% include policies in syllabi) and student preferences suggests that university messaging regarding syllabi verbiage on GenAI policies has been impactful.

Perceptions of Impact and Academic Integrity

Students and faculty differed greatly in their perspectives on GenAI's impact on learning. Students responded clearly above the neutral midpoint ($M = 4.0$, $SD = 1.1$), indicating genuine optimism about GenAI's potential. Faculty, however, fell below neutral ($M = 2.8$, $SD = 1.1$), reflecting a more skeptical or cautious stance. This difference of 1.2 points was statistically significant ($p < .001$). Student optimism may stem, in part, from students' ability to distinguish between appropriate and inappropriate uses of GenAI and embracing it as a legitimate learning tool for tasks like brainstorming, studying, and editing, while still recognizing its misuse in high-stakes assessments. Regarding academic integrity, students showed a sophisticated understanding of when GenAI use might constitute cheating. The highest percentages viewed GenAI use as cheating or plagiarism when used for in-class exams/quizzes (84%), writing complete papers (81%), and take-home exams/quizzes (74%). However, students were much less likely to view GenAI as inappropriate for brainstorming (18%), serving as a study assistant (17%), or editing papers (29%).

Both students and faculty recognized the growing importance of GenAI in the workforce, though faculty tended to rate each item more highly than students. As illustrated in Table 4, the

most strongly endorsed item among students was that knowing how to use GenAI will be an important skill in the workforce ($M = 3.4$, $SD = 1.4$), followed by anticipated personal use of GenAI in the future ($M = 3.2$, $SD = 1.5$). Faculty agreed even more strongly on both points ($M = 4.2$, $SD = 1.0$ and $M = 3.9$, $SD = 1.1$, respectively), suggesting that those already in professional roles may have a clearer sense of the magnitude for which GenAI is reshaping the workplace. While students acknowledged some belief that GenAI would improve their work ($M = 2.8$, $SD = 1.4$) and benefit humanity ($M = 2.6$, $SD = 1.3$), both ratings fell below the scale midpoint, suggesting a degree of uncertainty. This contrasts with faculty who were modestly more positive on both counts ($M = 3.4$ and $M = 2.9$, respectively).

Table 4

General Opinions of GenAI (Student $n = 2,538$; Faculty $n = 148$).

Opinions	Student		Faculty	
	Mean	Standard Deviation	Mean	Standard Deviation
Knowing how to use GenAI will be an important skill in the workforce**	3.4	1.4	4.2	1.0
I think I will use GenAI technology in the future**	3.2	1.5	3.9	1.1
I believe that GenAI will improve my work**	2.8	1.4	3.4	1.2
I think GenAI technology is positive for humanity*	2.6	1.3	2.9	1.2
I think many jobs in my field will be negatively impacted by GenAI*	2.4	1.2	2.7	1.2

* $p < .01$ ** $p < .001$

Main Benefits of GenAI

Both faculty and students were asked to report what they believe are the main benefits of Generative AI in academia. The student survey, administered first, was an open-ended question. Because of the time-consuming nature of thematic analysis of open response questions, a multiple response question was provided for faculty that included top themes from the previous faculty survey, along with opportunities for faculty to include “other” options, as needed. Student responses included 2,089 unique respondents. Responses were thematically coded where one student response could include multiple themes, if they mentioned multiple benefits in their response. Faculty responses included 142 unique respondents, with multiple (check-all-that-apply) responses possible. Sixty-six percent (66%) of faculty indicated that GenAI increased productivity or saves time, 58% believed that it enhanced information access, 52% perceived it was on the cutting edge of technology, and 30% saw increased teaching effectiveness as a benefit. The top benefits of GenAI themes from the student responses were provided clarification/more detail on topics ($n = 376$), utilize GenAI for studying ($n = 232$), brainstorming ($n = 209$), saves time/speed of information received from AI ($n = 201$), editing/grammar/spelling ($n = 186$), and automate repetitive tasks ($n = 109$).

Main Challenges of GenAI

Additionally, faculty and students were asked their perceptions regarding the main challenges of GenAI. Similar to the benefits format, the student question was open-ended with 2,148 unique responses that were thematically coded; the faculty survey was “select all that apply” with 142 faculty respondents. Eighty-three percent (83%) of faculty indicated using AI to bypass thinking was a challenge, as well as 82% answered regarding ethical concerns (e.g., biased algorithms, fairness in access), 76% indicated AI demonstrated inaccurate output, and 70% selected privacy concerns (e.g., data privacy, intellectual privacy). The top challenges of GenAI themes from the student responses were inaccurate output ($n = 725$), cheating/plagiarism/academic integrity ($n = 550$), using AI to bypass thinking ($n = 482$), overreliance on GenAI ($n = 276$), and GenAI diminishes creativity ($n = 200$).

Discussion

With the rapid growth of Generative AI use in higher education, we set out to establish longitudinal research examining student and faculty perceptions and uses of this technology, specifically focused on teaching and learning. This study provided the foundation of our baseline data for measuring the growth and impact of GenAI on instruction at our institution. While our research was intended to inform faculty development and support structures on our campus, our findings may help inform others in the field. Several findings were particularly interesting.

The Familiarity-Usage Paradox

The substantial gap between familiarity and use of GenAI among students was surprising. Although 88% of students reported strong familiarity with GenAI concepts, nearly half (48%) reported that they were not currently using these tools for academic work. This challenges a common assumption that students are embracing GenAI and heavily using it for their coursework, aligning with prior research and finding similar low usage among students (Kim et al.'s, 2025; Shaw et al., 2025.). Uncertainty and a lack of comfort (only 22% of student non-users reported feeling comfortable with GenAI) may moderate their use of the technology.

Faculty also indicated high familiarity with AI, yet only a minority reported systematically integrating GenAI into their teaching. Barriers such as concern regarding student cheating, comfort with the technology, and foundational skill development in discipline-specific uses of GenAI impact their use. Concerns focused on students' dependency with AI as well as its impact on their original thought and critical thinking. Recent research by College Board researchers found similarly that 45% of faculty were negative regarding GenAI use in higher education, with negative attitudes varying by faculty use of AI, discipline, and institutional selectivity (Angehr et al., 2026). Prior adoption research historically points to perceived usefulness, trust, and institutional culture as being predictors of implementation of a technology as opposed to awareness alone (Davis, 1989; Venkatesh & Davis, 2000; Rogers, 2003).

Diverging Views on GenAI's Impact on Learning

Students rated GenAI's potential impact on learning highly ($M = 4.0$), while faculty were significantly lower in their views ($M = 2.8$). This mirrors prior research findings (e.g., Kim et al., 2025; Slepchuk & John, 2025) and may be impacted by students' experience in using GenAI as an immediate support tool, where faculty tend to focus on its long-term impact on students'

critical thinking and cognitive development. This gap indicates the need for both faculty development and guidance regarding GenAI's uses but also points to the need for clear course policy guidelines. The disparity between student and faculty views can result in complications when faculty restrict what students view as legitimate learning support tools, or do not clearly articulate to students what they view as valid concerns and restrictions around GenAI use. Mixed or extreme variation across courses and faculty can present students with a challenge when one course embraces appropriately depicted GenAI use, and another outlaws it entirely. To ameliorate confusion, clear, detailed guidance needs to be provided in course syllabi campuswide so that there is no miscommunication with varying course requirements and students understand academic misconduct versus appropriate use. Faculty development and support units need to be aligned with recommendations for reporting GenAI guidelines to students through the syllabus and their instructional messages.

Students as Strategic Users of GenAI

Students' academic uses of GenAI were sophisticated, with clear distinctions between task context and risks involved. For example, the majority of students viewed GenAI use in high-stakes assessments such as exams or writing full papers as cheating. However, less than 20% viewed using GenAI for lower-stakes brainstorming, editing, or as a studying tool as inappropriate. This supports Lund et al.'s (2025) findings and suggests that students are applying a lens of academic integrity based on context to their use of GenAI. This also reiterates the need for context-specific guidelines for students, presented in course syllabi, to ensure that their beliefs align with the course requirements. It further points to the need for context-specific faculty development to ensure that faculty understand the complexity with which students are viewing the use of GenAI.

Both students and faculty perceive the workforce relevance of GenAI with 52% (M=3.4) of students and 80% (M=4.2) of faculty believing that GenAI skills will be important in the workforce. As faculty feel more strongly about AI's future workplace relevance for their students, this may be the future bridge that allows hesitant faculty to strategically integrate the technology into their instruction.

Faculty Concerns and Development Needs

Faculty expressed a desire for GenAI guidance and support, with only 5% indicating they did not need additional support. A large percentage of faculty mentioned a need for assistance on designing AI-resistant assessments, integration strategies, and addressing academic integrity issues. While overall GenAI literacy is valuable, these findings indicate targeted professional development is needed focusing on pedagogical and policy issues related to GenAI.

One of the most notable findings was the misalignment of faculty implementation of GenAI in their courses and student experience with its use. While 33% of faculty indicated they were encouraging GenAI exploration in all their courses, nearly half (48%) of students indicated they were never encouraged to do so by faculty. Similarly, 18% of faculty reported that they teach GenAI contextual use in their courses, yet 76% of students reported no instruction in its use.

Faculty trepidation over students' use of GenAI—general discomfort, opposition, academic integrity concerns, and a belief that fundamental skills should come before its use—point to areas that need more guidance and direction that require faculty development and a strong campus support structures.

Limitations

Several limitations should be considered when interpreting the findings of this study. First, the data were drawn from a single institution—a large, research-intensive (R1) university—which, despite its size and demographic diversity, may not fully represent the broader landscape of higher education. Furthermore, faculty participation varied across colleges, resulting in samples that were not proportionally representative of all academic units. Consequently, while the findings offer meaningful insights into faculty perceptions and behaviors at this type of institution, their generalizability to other institutional contexts, such as community colleges, liberal arts institutions, or smaller teaching-focused universities, should not be assumed without further empirical validation.

Second, the study relied on self-reported survey data to capture faculty and student perceptions and behaviors related to GenAI use, rather than direct observation or objective behavioral measures. As with all self-report methodologies, responses may be subject to social desirability bias, recall limitations, or inconsistent interpretation of survey items. This concern is particularly salient in the context of GenAI, where both faculty and student usage may intersect with evolving and sometimes ambiguous institutional policies on academic integrity, potentially leading respondents to underreport or mischaracterize their actual practices. Future research would benefit from triangulating self-reported data with direct behavioral measures, such as learning management system logs or institutional usage analytics, to better capture the full picture of how both populations are engaging with these tools.

Third, the rapid pace of development in the GenAI landscape poses a significant challenge to the longevity and relevance of the present findings. The availability of new tools shifts in institutional policy, and changes in both faculty and student attitudes and behaviors are all evolving concurrently, meaning that findings current at the time of data collection may become outdated relatively quickly. Given that faculty and student adoption trajectories may diverge, with each population responding differently to emerging tools, incentives, and institutional guidance, longitudinal and repeated cross-sectional research designs will be essential for tracking how these distinct but interrelated patterns of adoption and institutional responses develop over time.

Finally, this study was designed to capture a snapshot of current usage patterns and proximate support needs and was therefore not positioned to assess the longer-term pedagogical or institutional implications of GenAI integration. Critical questions remain regarding the relative effectiveness of different integration approaches, their influence on student learning outcomes, and their broader impact on faculty workload and professional identity. These questions represent important directions for future inquiry.

Conclusions and Recommendations

This study presents a baseline of student and faculty GenAI use, perceptions, and familiarity with GenAI's use in our institution. However, it also indicates that this technology is in a state of flux at our university, presenting opportunities for targeted support, faculty development, policy, and future research. Faculty indicate a pressing need for targeted, practical guidance regarding GenAI's use in the classroom with several pedagogical challenges including assessment design, integrity, and discipline-specific integration, being critical. Course level policies need to take into account the sophistication of students' ethical reasoning around GenAI use. Students navigate this technology in a patchwork of institutional, college, and course-level expectations. Clear, consistent messaging—beginning at syllabus level in courses—can help reduce confusion and the potential for unintended misconduct. Campus messaging needs to ensure that is the expectation for all faculty. While faculty have autonomy over their course AI policies, to meet state requirements they must have an AI policy stated in their syllabus beginning Summer 2026.

Future Research Needs

The rapid pace of GenAI development points to the need for longitudinal, ongoing research to capture shifting norms and highlight stable trends as the technology progresses throughout the educational and workplace ecosystems. Discipline-specific findings need to be examined as well, with guidance provided for appropriate and encouraged uses for students, based on skills needed for the workplace. In addition, research on faculty and students' definitions and interpretations of what constitutes academic misconduct is needed to ensure alignment. The impact of expanding GenAI access and literacy is also needed. More challenging is research examining the impact of GenAI on students' critical thinking skill over time. GenAI has the potential to disrupt many norms. Perhaps most urgent is scholarship on new, Gen-AI-resistant, discipline-specific and scalable assessments.

Given the speed with which AI is being integrated into numerous commonly used tools (e.g., library search tools, and general search engines), it is quickly becoming impossible to outlaw all use of GenAI in teaching and learning. Both faculty and students need guidance and support on how to approach thoughtful and appropriate use of this highly disruptive technology. Overall, institutions will need to move toward proactive pedagogical innovation rather than merely reactive detection.

Declarations

Acknowledgments

The authors wish to thank the faculty members and students of the University of Central Florida who volunteered to participate in the GenAI surveys.

Ethics Statement

This study was conducted in accordance with recognized ethical standards. Informed consent was obtained from all participants, and data was collected and reported with respect for confidentiality and anonymity. The study protocol was reviewed and approved by the

Institutional Review Board of University of Central Florida, Approval No. 00006957 (student survey) and 00006717 (faculty survey).

AI Use Statement

Generative artificial intelligence (GenAI) platforms, ChatGPT and Claude, were used to support the summarization and synthesis of peer-reviewed literature obtained through systematic database searches, brainstorm verbiage related to findings, and to improve the clarity of selected passages. The use of this tool did not extend to data collection, analysis or interpretation. All AI-generated content was reviewed, revised as necessary, and approved by the authors, who assume full responsibility for the accuracy and integrity of the work.

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Graduate Teacher Education Students Evaluate Generative AI: A Two-Year Comparison

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Abstract

Artificial intelligence (AI) has been evolving since the middle of the 20th century. During the latter part of the 20th century and into the 21st century, most AI programs remained within the realm of computer science and psychology. However, when OpenAI launched its generative AI program, ChatGPT, using large language modelling (LLM) software, the world took notice and AI expanded beyond the computer science and psychology fields of study. ChatGPT and other generative programs such as Google's Gemini and Anthropic's Claude AI exploded on the scene and brought AI to the masses. Without a doubt, the emergence of AI has had repercussions in all walks of life, including education. The purpose of this study is to report on the opinions and use of AI by K-12 teachers enrolled in a graduate education leadership program over the course of two years. Beginning in Spring 2023, when ChatGPT first attracted public attention, qualitative data was collected from the teachers enrolled in courses taught by the author. The main purpose of this data collection was to determine if opinions of AI changed during the two years that data were collected. All those enrolled in this program have master's degrees in education and experience as teachers in New York City schools.

Keywords: Artificial intelligence, generative AI, graduate teacher education, qualitative research

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Artificial intelligence (AI) has been evolving since the middle of the 20th century. Luminaries such as Alan Turing and Herbert Simon (Nobel Laureate Economics, 1978) made significant contributions to the field starting in the 1950s. During the latter part of the 20th century and into the 21st century, most AI programs remained within the realm of computer science and psychology. However, the past twenty years have brought major AI development as American corporations such as Alphabet (Google parent company), Microsoft, Apple, Nvidia and Amazon started investing billions of dollars in this technology. Internationally, well-funded companies in China such as Baidu, Tencent, and Alibaba have been challenging American hegemony in AI development. These investments bore fruit in 2022, when OpenAI launched its generative AI program, ChatGPT, using large language modelling (LLM) software. ChatGPT and other generative programs such as Google's Gemini and Anthropic's Claude AI exploded on the scene and brought AI to the masses. Indeed, "AI" was named the word of the year for 2023 by Collins Dictionary (BBC, 2023). In 2025, *Time* named the "Architects of AI" as its 2025 Person of the Year for their profound impact on the world (Jacobs, 2025). Without a doubt, the emergence of AI has had repercussions in all walks of life including education. The purpose of this study is to report on the opinions and use of AI by K-12 teachers enrolled in a graduate education leadership program over the course of two years. Beginning in Spring 2023, when ChatGPT first attracted public attention, qualitative data was collected from teachers enrolled in courses taught by the author. One of the assignments of these courses was to use and evaluate AI as a tool for completing an essay assignment. Forty-five (N=45) students participated in this evaluation. The main purpose of this data collection was to determine if opinions and use of AI had changed during the two years that data were collected. All those enrolled in this program have master's degrees in education and experience as teachers in New York City schools. Their training and experience give them keen insights into pedagogical practice, making them ideally suited to evaluate generative AI as an instructional tool. This article will report on their evaluations.

Definition of Terms

It is important to define generative AI for the purpose of this article as well as to distinguish it from general AI. AI is a broad field of science in which machines are taught to develop humanlike capabilities. General AI occurs at the point when AI can learn human cognitive skills (Suleyman, 2023) and is still years away from full development. A recent term "agentic AI" has evolved and is related to general AI. The primary difference is that agentic AI is a more specific application. It is proactive, autonomous, and adaptive, capable of planning, reasoning, and taking specific complex actions independently to achieve objectives in dynamic environment. Agentic AI applications are actively being developed and are evolving rapidly. Generative AI, on the other hand, is here now. It is a technology within the field of artificial intelligence that utilizes neural networks, which mimic the human nerve system, to generate new and original content. It can produce a wide variety of data, including text, images, audio, and video. Generative AI can also create content such as synthetic data, code, simulations, and more by identifying patterns and structures within existing data. Generative AI builds upon technologies like large language models (LLMs), which are trained on vast amounts of data, enabling them to predict and develop data such as original images or text structured in sentences and paragraphs.

This study focuses specifically on the use of generative AI programs currently being used by millions of people throughout the world. Large language models (LLM) are based on the concept of a *transformer*, first introduced in 2017 by researchers at Google (Vaswani, et al, 2017). A transformer derives meaning from long sequences of text to understand how different words or semantic components might be related to one another, then determines how likely they are to occur in proximity to one another. These transformers are run unsupervised on a vast corpus of natural language text in a process called *pretraining* before being fine-tuned by human beings interacting with the model.

Generative AI and Education – A Literature Review

Since ChatGPT's debut in 2022, generative AI has been a major topic of discussion in all walks of life including education. Just three years later, one study (Freeman, 2025) reported that the use of generative AI is “soaring” in higher education with 92 percent of undergraduates using it in one form or another. As a result, planning, development and policy issues are permeating in educational institutions regarding the integration of AI into instruction and other activities. At first blush, the knee-jerk reaction to generative AI was an attempt to contain it, especially amid concerns about plagiarism. However, this view is quickly evolving, with many schools trying to figure out ways to harness it as a potentially helpful technology for teaching and learning. A growing research base is evolving mostly in the form of reviews of its deployment in education. For example, (Bahroun, Anane, Ahmed, & Zacca, 2023) in a review of 207 papers concluded:

This review paper presents a comprehensive analysis of generative artificial intelligence (GAI) in education... This study begins with a content analysis that explores GAI's transformative impact in specific educational domains.... The versatile applications of GAI encompass assessment, personalized learning support, and intelligent tutoring systems. Ethical considerations, interdisciplinary collaboration, and responsible technology use are highlighted, emphasizing the need for transparent GAI models and addressing biases. Subsequently, a bibliometric analysis of GAI in education is conducted, examining prominent AI tools, research focus, geographic distribution, and interdisciplinary collaboration. ChatGPT emerges as a dominant GAI tool, and the analysis reveals significant and exponential growth in GAI research in 2023. Moreover, this paper identifies promising future research directions, such as GAI-enhanced curriculum design and longitudinal studies tracking its long-term impact on learning outcomes. These findings provide a comprehensive understanding of GAI's potential in reshaping education and offer valuable insights to researchers, educators, and policymakers interested in the intersection of GAI and education.(Bahroun, Anane, Ahmed, & Zacca, 2023, p. 1)

Other reviews (Mao, Chen, & Liu, 2023; Ahmad, Murugesan, & Kshetri, 2023; Taniga, 2023) have a similar focus and conclude that generative AI is enjoying increased use by faculty and students alike. An important area of concern regarding the use of generative AI is whether the “human” element of teaching and learning may be compromised (Henane, 2023; Lo, 2023; Global Services in Education, 2023) These authors raised pedagogical questions related to the social and emotional aspects of learning. For example, Henane (2023) commented that “AI may excel in numerous tasks, but it will never possess the capacity to teach a child how to love, care,

express their feelings, and develop their unique personality.” (Henane, 2023) Parra and Chatterjee (2026) likewise emphasized that, considering AI, teachers need to maintain human connections and sociocultural responsiveness. In an article examining “critical conversations” in AI, they concluded, “We need to focus on the humans and the relationships.” (Parra & Chatterjee, 2024, p. 10)

It is not possible in this short article to review all the possible uses of generative AI in instruction because subject matter and teaching approaches would dictate how to use it most effectively. For instance, in a writing or essay assignment, students might be encouraged to use generative AI if they cited text appropriately. In science courses, generative AI can make available access to simulations, images, and other media to provide graphic insights into biological, chemical, and physical processes. In professional courses, such as health, nursing, law and social work, generative AI can be used to develop case studies with multiple outcomes. Using generative AI does require a certain amount of trust in students, but faculty have been concerned about this issue for years given the plethora of material that exists on the Internet and the search capabilities of engines such as Google. This is evident from the proliferation of plagiarism detection software such as Turnitin now routinely made available on all major course and learning management systems. In sum, generative AI, with its ability to create new text, code, images, and more, can be a tool in the classroom for both students and teachers. Here are several pros and cons.

Pros for Students

Brainstorming and Creativity: Students can use generative AI to get ideas flowing for projects, essays, or presentations. AI can generate different scenarios, characters, or plot points to jumpstart creative thinking.

Personalized Learning: AI tutors can provide students with individualized practice problems, quizzes, and explanations tailored to their specific needs and learning pace.

Language Learning: AI chatbots can converse with students in a foreign language, helping them practice speaking, listening, and comprehension in a safe and engaging environment.

Writing Improvement: Generative AI can help students overcome writer's block by suggesting ideas, generating outlines, or even creating drafts that students can then edit and improve.

Pros for Teachers

Content Creation: AI can streamline lesson planning by generating quizzes, worksheets, or practice problems based on specific learning objectives.

Accessibility Tools: AI can create alternative formats for learning materials, such as audio versions of text or captions for videos, making them more accessible to students with disabilities.

Differentiation: Teachers can use AI to create different versions of assignments or learning materials to cater to students with varying learning styles and abilities.

Feedback and Assessment: AI can help automate the grading of some types of assignments, freeing up teachers' time to provide more personalized feedback to students.

Pros and Cons of Generative AI in Education

Plagiarism and Cheating: Students might misuse AI-generated content by plagiarizing or using it to complete assignments without understanding the material.

Over-reliance and Critical Thinking: Students may become overly reliant on AI for content creation, hindering the development of critical thinking and research skills.

Bias and Misinformation: AI models are trained on data, and if that data is biased, the AI-generated content can also be biased or contain misinformation.

Teacher Role and Job Security: There are concerns that AI could replace some of the roles traditionally filled by teachers, leading to job insecurity.

Ethical Considerations: The use of AI in education raises ethical questions about data privacy, student ownership of work, and the potential for algorithms to perpetuate bias. (Google, (2024))

The above list was generated by the *Gemini* generative AI software on June 3, 2024. I agree with its comments and conclusions.

Methodology

This study uses qualitative research to evaluate generative AI as an essay writing tool. Elements of Creswell's (2009) characteristics for qualitative research were utilized as follows:

- the use of a natural (class) setting;
- collect multiple sources of data;
- researchers as instruments;
- inductive data analysis; and
- participants' meaning. (Creswell, 2009)

The participants in this study were enrolled in a required graduate course in the Administration and Supervision Program at Hunter College. The program has selective admission requirements as follows:

A master's degree from an accredited institution with a Grade Point Average (GPA) of at least 3.0.

Permanent or professional New York State (NYS) certification as a teacher and/or pupil personnel service provider within grades PreK-12.

A minimum of three years of approved teaching and/or school service within grades PreK-12 under regular appointment (or its equivalent for counselors, social workers, and school psychologists) or two years approved teaching and/or school service and at least one year of relevant management/leadership experience.

The students in this program were generally well-organized, focused on their studies, and had good writing skills. Enrollment in this course was as follows: Spring 2023 (N=15), Fall 2024 (N=13), and Spring 2025 (N=17), for a total N=45 study participants.

The basic characteristics of these students were:

Gender: 34 females; 11 males.

Teaching Level: 23 high school teachers; 11 middle school teachers; 11 primary school teachers.

Average Age: 32.3 yrs.

Average teaching experience: 9.5 years.

In each case, students were given an assignment to write an essay using ChatGPT, Gemini, or any other generative AI software program with which they were familiar. Out of 22 students enrolled in Spring 2023, seven students did not wish to use a generative AI to write their essay. The author allowed this, leaving an N=15 for the comparison. Although the seven students made no explicit comments for the study, their reluctance might be construed as further evidence regarding the opinions about generative AI at the outset.

To provide a supportive environment, the author provided a one-hour introduction to generative AI using ChatGPT as an example geared to the essay assignment. Students were free to ask any questions about the assignment including the use of a generative AI program. During the semester, several student progress sessions were conducted during which students could ask any questions they had about the assignment.

The two major data collection tools for this study were the student essays and focus group discussions. Student essays required them to answer a series of questions related to their experiences using generative AI (see Appendix A). In addition to preparing the written essay, students participated in a two-hour focus-group discussion after they completed their assignments. Student responses to the questions on the essay and comments made during the focus group discussion were the sources of data for this study.

Findings and Discussion

The first major finding in this study was that over the two years of data collection, most students had begun to use generative AI in preparing their lessons or for other school-related activities. During the initial data collection in Spring 2023, only one student of the fifteen participants had previously used generative AI. By Spring 2025, almost all students used it to

some degree. Several indicated that their school districts had initiated staff development activities. The following represent examples of student comments. They are not meant to be all-encompassing reporting of everything the students stated.

Using AI

I frequently use generative AI to assist in planning my math lessons. I typically use Magic School. I attended a workshop that was offered by my school this September on Superintendent's Conference Day. It has become an invaluable resource in my teaching. When I have a specific math standard in mind, I often type that standard into AI and request differentiated word problems or multi-step word problems. This allows me to generate a variety of problems that cater to the diverse learning needs of my students, ensuring that each student can engage with the material at their own level. (Student RDD, Spring 2025)

This school year, we have been experimenting with the use of AI to improve instruction. Specifically, we have used Microsoft Co-Pilot, ChatGPT, and Magic School AI. So far, we have found that Magic School AI is by far the most effective and efficient AI tool. While the scope of this experiment is small and in its early stages, initial findings indicate that AI's greatest value lies in supporting teachers rather than replacing their expertise. (Student TII, Spring 2025)

My perspective began to change when our school invested in a dedicated program called Toddle AI, which is specifically designed to support teachers in developing comprehensive and effective lessons. Although I found Toddle AI to be a powerful tool with a wide array of features, its complexity was a bit overwhelming at first. I was still hesitant to fully rely on AI for all aspects of my teaching until I encountered another practical application—drafting report card comments. (Student HJJ, Spring 2025)

This assignment showed me that I am completely underutilizing AI in my practice. There are so many times I'm making things from scratch or starting from nothing. Knowing my personality, I'm sure there will always be things about lessons that AI gives that I would tweak or change, but it can provide me with a really solid foundation that can be applicable in my planning process and in my practice. (Student MMJ, Spring 2025)

The comments above indicate that school districts are taking a more proactive role in 2025 in providing professional development opportunities for teachers to evaluate and use generative AI software. In addition, school districts are moving beyond generic AI programs such as ChatGPT and Gemini and are using AI programs such as Magic School and Toddle AI that are designed specifically for teachers.

Second, in the first data collection in Spring 2023, several students indicated that generative AI could be of benefit to particular student populations such as students with special needs and ESL learners. Below is a comparison of comments regarding using generative AI for students with special needs.

Special Education Students

Some of my co-workers have been utilizing ChatGPT *to create IEP goals for their students*. I was amazed with how capable it was at any task it was given, which is why I wanted to utilize it for this assignment. (Student KAA, Spring 2023)

I regularly use Magic School AI to assist with differentiating lessons for my special education students. For instance, I utilize its text-leveling and text-summarizing tools to adjust the Lexile levels of reading materials, making them more accessible for diverse learning needs. (Student OKK, Spring 2025)

I work in a school where 100% of the students are deaf and deaf disabled, so I almost did not include 'deaf' in my search because I figured Chat GPT would not be able to create a lesson plan for deaf students. But while looking over the plan, they incorporated American Sign Language into the lesson and at a very appropriate level that I would have done (introduction to 'family' and 'community words' in sign language as well as family-related signs). Also, deaf students and deaf students with disabilities rely heavily on visual aids, and ChatGPT made sure to include this repetitively throughout the daily lessons. The lessons also specifically stated on the bottom 'This plan uses visuals, interactive elements, and sign language to ensure engagement and learning for deaf kindergarten students.' (Student BLR, Spring 2025)

This was my first experience ever using generative AI for the purpose of instructional planning. I chose the prompt because I currently work as a special education teacher teaching a hydroponics lab to students with autism. I work in the most restrictive setting in the New York City Department of Education, meaning that the student to teacher ratio is the lowest possible by law (6:1). Having never previously used generative AI to create educational content, this experience was something that I entered into without any preconceived ideas about what to expect using the software. After several detailed prompts, the AI produced a lesson plan that had both strengths and weaknesses in the final product. (Student GPP, Spring 2025)

ESL Students

The majority of the students I teach are newly arrived ESL in the United States, as such, writing often causes them anxiety. By using this technology to brainstorm assignments, it would show them how to write a basic essay and not stare at a blank page, perplexed by what they have to do. (Student MEE, Spring 2023)

As a teacher juggling many demands from district initiatives to guidance from administration to a variety of student needs, using generative AI to help with lesson planning has been a valuable resource that I use from time to time. Teaching special education and working in a school with concrete ELA/ Writing lesson structures using generative AI has been incredibly helpful in advising me when feeling stuck on a lesson or when needing to approach a lesson differently. At this time, I use AI to support my lesson planning in ESL as my school currently uses a general education curriculum for reading instruction. (Student CAA, Spring 2025)

The second prompt I asked ChatGPT was: ‘Include strategies for English Language Learners.’ The initial prompt produced a module with differentiation and strategies to support ELLs. When asked ChatGPT to produce strategies for ELLs, the AI bot shared the following strategies:

- Use visuals and manipulatives, visual vocabulary support
- Simplify and repeat instructions
- Use sentence frames and prompts
- Scaffold learning with small group instruction
- Employ peer support and cooperative learning
- Incorporate real-life contexts
- Provide time for oral and written practice
- Use technology and interactive tools

The response also included a few suggestions for which ELL strategies to use on each of the five lesson days. Overall, the plan offered was universal and did not go in-depth. I agree that visuals and repeated instructions, language frames, small groups, and technology are all strategies that support ELLs and all learners. However, why did the initial prompt not provide these universal strategies for learning? For example, visual strategies support all learners. But if we specifically pair a visual with a word label in multiple languages, it is a more contextualized support. (Student ABB, Spring 2025)

The above comments indicate that in Spring 2023, teachers thought that generative AI might be of use in the future. By Spring 2025, generative AI, in fact, was in regular use. During the focus group sessions, the number of comments about the benefits of generative AI for special education students was of particular interest. Students were adamant in what they saw as benefits of a generative AI tool for applications involving students who struggle with writing in general, for ESL students, and for special education students.

The final area of comparison between the students in these courses has to do with whether they would allow their own students to use generative AI. The students in Spring 2023 were fairly consistent in limiting use by their students who were in earlier grades versus those in high school. Here is a sample from the Spring 2023 participants:

I am a second-grade teacher, so ChatGPT isn’t very relevant. (Student LRR, Spring 2023)

I would consider allowing students in my high school classes to use this for writing assignments, but I would hesitate with my middle schoolers. We already have a ton of plagiarism issues because the students don’t fully understand how to use sources instead of copying/pasting google searches. (Student OMM, Spring 2023)

I teach International Baccalaureate History (High School) and recently the IB established a policy allowing students to use and cite ChatGPT in their writing. As a result, I would allow students in my class to use it for their work as long as they follow the proper parameters in citing the work. (Student WPP, Spring 2023)

And a sample from Spring 2025 participants:

I would certainly allow (First Grade) students to use AI for certain lessons and projects if it didn't interfere with them learning a key skill. Nonetheless, using AI would be challenging for some students as they aren't all able to spell or speak at this time. However, my students could instead use their devices to request the information they are looking for. I could have students use their devices to tell me what facts they are looking for, which I or another staff member could input into the AI. (Student CCA, Spring 2025)

While I do not yet allow my (High School) students to utilize generative AI for assignments, I have encountered students using it, and it has been fairly obvious to me when they do. One of the most significant concerns I have about allowing students the use of these technologies is that by relying on AI, they are not developing the essential skills of reading and writing for themselves. (Student GII, Spring 2025)

With the addition of 11 AP (High School) courses in my school and opportunities for students to take advanced Regents exams early, AI has become a tool students are leveraging for assignments. Student use of AI spans a wide spectrum, from submitting AI-generated first drafts to using it as a tool to refine and edit their own writing. In response, we are developing guidelines to ensure AI use enhances rather than replaces student thinking. (Student TII, Spring 2025)

I'm torn on the idea of using generative AI as a student-facing tool in elementary school. I'm hesitant because my students are still building foundational skills across all academic areas, and I worry that using generative AI could hinder their natural academic growth by offering shortcuts instead of promoting critical thinking and independent problem-solving. Also, at this age, children are just beginning to learn how to use technology in productive and safe ways. Any future use of generative AI with students would require careful thought and planning to ensure they use it in meaningful and productive ways—though maybe generative AI could even help with that! (Student HHJ, Spring 2025)

I have not yet permitted students to use artificial intelligence (AI) for completing assignments; however, I have observed them using AI tools to navigate their academic work. While AI may offer students efficiency in completing tasks, its overreliance contributes to significant academic deficits. Using AI to complete assignments often leads to students performing below their potential. In my experience, the 11th-grade students I teach typically read and write at levels between 5th and 8th grade, and using AI to generate responses helps them maintain their academic capacity but does little to improve it. When students use AI for assignments, it becomes a normal and dependent behavior that discourages critical thinking, diminishes attention span, and reduces resilience. As such, it would be beneficial to teach students how to navigate AI responsibly, integrating it as a tool for learning without allowing it to replace essential cognitive skills. (Student OKK, Spring 2025)

The comments above indicate that the students enrolled in Spring 2025 are more familiar with the nuances of generative AI and appear to be making more informed decisions as to whether they would allow their students to use it. While recognizing certain efficiencies using AI, they are also concerned and cautious about broader cognitive developmental issues.

Conclusion

In this article, data were presented comparing how graduate students, themselves teachers, are developing positions and attitudes about the use of generative AI to support their students or their teaching. An appropriate interpretation of the data is that after two years, teachers have developed a far-more informed and sophisticated knowledge of generative AI as they contemplate their own and their students' usage of this technology. In those two years, Generative AI platforms have also proliferated, and more are now available which were specifically created to help teachers. We need to keep in mind that we are still in the beginning stages of the integration of AI into our lives and organizations, including schools. The next decade will see the evolution of full-blown general AI. In November 2024, the author was on a panel discussing the future of AI and received an email from one of the attendees who asked: "What will all this technology do?" I answered him by saying that his was the wrong question. The right question is: "What will all this technology NOT do?"

Declarations

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Institutional Review Board Consent This project was reviewed by the City University of New York Institutional Review Board. Informed consent was obtained from all subjects involved in the study.

Conflicts of Interest

The author declares no conflict of interest. The manuscript avoids promotion of specific products in the research (e.g. "proving" the effectiveness of a single tool or product).

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Appendix A

To complete this assignment, students are to use a generative AI program such as ChatGPT or Gemini. You are free to include as much of the AI generated text into your paper as you wish as long as you cited it accordingly. And at the end of your paper, please include a paragraph(s) on your experience with using generative AI in this assignment answering the following:

- a) Have you used generative AI previously? If so, how did you use it?
- b) Do you feel the AI program produced good-quality material for your paper?
- c) Do you allow students in your own classes to use generative AI for assignments. And if yes, what has been your experience in allowing students to use it?

Asked & Answered: Using AI to Nudge Student Metacognition and Responsibility for Learning

John Fritz, Assoc. Vice President, Instructional Technology
 Josh Abrams, Instructional Technology Design Specialist
 Sarah Bass, Associate Teaching Professor, Chemistry
 Suzanne Braunschweig, Teaching Professor, Geography and Environmental Systems
 Tara Carpenter, Teaching Professor, Chemistry
 Nancy McAllister, Assistant Teaching Professor, Interdisciplinary Science Program
 Thomas Penniston, Coordinator of Learning Analytics

University of Maryland, Baltimore County (UMBC)

Abstract

This reflective case study examines how the University of Maryland, Baltimore County (UMBC) is exploring the use of AI to personalize, scale, and nudge students to become more self-regulated learners. Specifically, four courses, varying in discipline, size, and use of technology, collectively share a common pedagogical goal of cultivating students' willingness and ability to learn how to learn through AI-assisted formative practice. For example:

- UMBC's largest two courses (CHEM 101 & 102), each with over 800 students annually, are using AI to create a "24/7 prof" and formative learning environment, based in part, on "spaced practice" to counter ineffective student cramming for exams. While effective, students struggle to replicate these strategies on their own in later courses. Can AI help?
- A lab science course for non-STEM majors (SCI 100), with 600 students annually, asks students to create their own practice questions AND answers for extra credit. While successful, AI could streamline the curation of these student-crowdsourced study guides, which could be key to faculty colleagues adopting the approach.
- A smaller course for students on academic probation (UNIV 102), with 20 students per section, is using AI to inform a team-based extra credit practice environment for weekly quizzes. This helps students form effective study groups, a skill valued by faculty but difficult to implement, especially for at-risk students.

In each use case, the goal is to use technology that provides students with a personalized learning environment—akin to a virtual "Holodeck" for practice—that refines their ability and willingness to honestly and accurately assess what they currently know, understand and can do, and close the gap between where they see themselves vs. where they'd like to be—especially after taking a high-stakes midterm or final exam.

Keywords: Pedagogical innovation; metacognition; generative AI; student responsibility for learning

Fritz, J., Abrams, J., Bass, S., Braunschweig, S., Carpenter, T., McAllister, N., & Penniston, T. (2026). Asked & answered: Using AI to nudge student metacognition and responsibility for learning. *Online Learning*, 30(1), 63-81. <https://doi.org/10.24059/olj.v30i2.5848>

Introduction

The *Enterprise* finds itself in a dire situation, ensnared by an ancient alien energy trap that threatens its destruction. Chief Engineer Geordi La Forge is tasked with the critical mission of reconfiguring the warp drive to escape, but he struggles with the original, complex blueprints. Faced with this formidable challenge, Geordi makes a **deliberate decision** to utilize the holodeck to “reason through the engine reconfiguration.”

The paragraph above is excerpted verbatim—with emphasis added—from a 12-page Google Gemini “Deep Research” study (“TNG holodeck self-directed learning,” 2025) that was prompted by the following: “Identify episodes of Star Trek: The Next Generation in which the holodeck is used for self-regulated, self-directed learning.” The analysis that follows is fascinating, on-point for this chapter, and well worth a closer read, especially as a metaphor for how AI might be used for self improvement. In fact, consider these holodeck personalized learning “principles” (p. 2), perhaps substituting the word “AI” for “holodeck”:

- **User Initiative:** The character actively chooses and initiates the use of the holodeck for a personal objective related to learning, skill development, or personal growth, rather than being assigned or compelled.
- **Active Engagement:** The character actively participates in and shapes the simulation, steering its direction, responding to its challenges, or modifying its parameters to achieve their specific learning goal. This is not passive observation.
- **Tangible Outcome:** The holodeck use leads to a discernible intellectual gain, a measurable improvement in a skill, or a significant step in psychological or personal development for the character.
- **Beyond Recreation/Mandatory Training:** The primary purpose of the holodeck engagement is not solely leisure or a pre-assigned Starfleet training exercise, but a self-driven pursuit of knowledge, mastery, or self-improvement.

However, lest we think personalized learning at scale can only occur in science fiction, consider the “one wish” by 2013 TED Prize winner Sugata Mitra. In his widely viewed TED talk, “Build a School in the Cloud,” (2013), Mitra shows how children in India spontaneously started teaching themselves and each other through an Internet-connected PC he installed in an abandoned ATM on the outside wall of his office building (dubbed the “hole in the wall”). He calls what he observed—and explicitly did not design or direct—a “self organized learning environment” (SOLE), which he then replicated in many different, impoverished locations throughout India (McTamaney, 2024).

While AI’s role in education is evolving, it is clear that the potential for personalized learning at scale is tantalizing. But what type of learning? If access to information is ubiquitous, do we really want students to just be passive recipients of canned lectures most often associated

with a “transmission” model of learning? Instead, how can we use technology to facilitate more of a “constructivist” model, where learners play an active role in sense-making and the application of knowledge? In this chapter we explore how AI is—or could be—empowering learners to master self-assessment, which is key to becoming self-regulated, life-long learners.

Methods

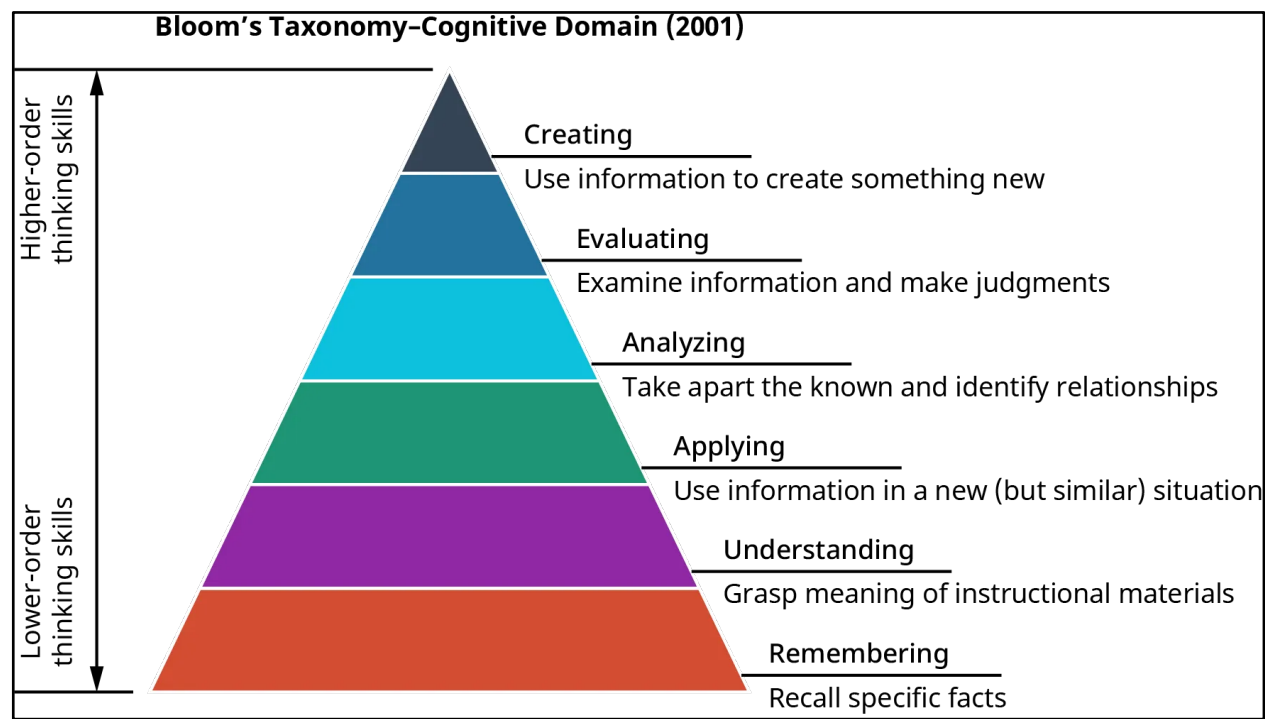
Metacognition as Pedagogical Framework Among Participating Faculty

As part of this case study on each course’s current or potential use of AI, we first provide a common pedagogical framework focused on metacognition (e.g., thinking about one’s own thinking), which has been influential to many UMBC faculty before, during and since the pandemic pivot to online learning.

Specifically, in 2016, UMBC’s Faculty Development Center (FDC) sponsored a book discussion about Saundra McGuire’s *Teach Students How to Learn: Strategies You Can Incorporate Into Any Course to Improve Student Metacognition, Study Skills, and Motivation* (2015). A year later, McGuire gave an on-campus keynote presentation (2017) at the annual “Provost’s Symposium on Teaching and Learning.” In both her book and UMBC talk, McGuire argued that faculty need to intentionally and explicitly introduce students to metacognition, or thinking about thinking, by showing and telling them about Bloom’s Taxonomy of Learning (Figure 1): “Don’t just assume they’ve seen Bloom’s [taxonomy] or understand it,” said McGuire, who also co-authored with her daughter, Stephanie, a student-focused book about metacognition, *Teach Yourself How to Learn* (2018).

Figure 1

Bloom's Taxonomy of Learning from UMBC's "Learning and Metacognition" Tutorial (2023)



“Reading [McGuire’s] book essentially changed the way I view teaching and learning and changed how I view course design,” says Tara Carpenter, Teaching Professor of Chemistry, who typically teaches CHEM 102 “Principles of Chemistry II,” and had long seen incoming students repeat what they were conditioned to do in high school: memorize, regurgitate (for an exam), and promptly forget (after it). “Most of them just aren’t prepared for the rigors of college because they simply don’t understand the difference between memorization and learning.”

This disconnect often stems from related habits of mind and practice that many students have not yet developed. For example, the “forgetting curve,” first identified by Hermann Ebbinghaus (2013a; Murre & Dros, 2015), shows that memorized information is lost exponentially over time unless reinforced through repeated exposure. Students frequently attempt to overcome this through cramming or mass practice study sessions, which results in poor long-term retention and cognitive overload. In contrast, spaced practice (or distributed practice), which Carpenter has long espoused (2023a; T. S. Carpenter et al., 2020a), involves structuring regular, smaller chunks of study to promote long-term proficiency and has been widely validated across STEM disciplines.

Additionally, for students to transition from reactive cramming to proactive learning, they must develop skill in “self-regulated learning” (SRL) skills. SRL is defined as a process where students are “metacognitively, motivationally, and behaviorally active participants in their own learning” (Zimmerman & Schunk, 2001, p. 5). Key to this mindset is the ability to accurately

assess what one knows and execute a plan to close those gaps. Research suggests that while students find spaced practice beneficial when supported by course structures, they often struggle to implement these habits independently due to challenges in time management and self-assessment.

Finally, as a technological precursor to Gen AI, adaptive learning technology serves as a natural complement to these pedagogical goals by scaling the identification and remediation of individual student weaknesses. Edwards et al. (2017) describe adaptive learning systems as ranging from simple rules-based structures to complex machine learning-based platforms that tailor formative practice based on a student's demonstrated performance. By integrating AI into this framework, faculty can reduce the significant time and effort required to curate large question banks for formative practice and manage personalized feedback. Effectively, AI could act as a socio-technical bridge, incorporating the principles of metacognition, spaced practice and self-regulated learning into a scalable environment that nudges students toward honest self-assessment and mastery.

In fact, both Carpenter and her colleague, Sarah Bass, Associate Teaching Professor of Chemistry, leveraged a large question-bank approach to online, "open note" exams curated during the pandemic (Bass et al., 2021a, 2021b; Fritz, 2020), becoming much more intentional about introducing students to metacognition. They also regularly delivered McGuire's recommended lecture on the topic, and took time in class to encourage student reflection on their own learning, especially after exams (T. S. Carpenter et al., 2020b). Bass and Carpenter, who frequently collaborate, tinker and brainstorm how their shared General Chemistry curriculum works across their courses, also worked on how to scale individual, personalized emails, highlighting effective strategies for specific students who seemed to be struggling or even succeeding (Bass & Carpenter, 2024).

Similarly, Suzanne Braunschweig, Teaching Professor in Geography and Environmental Systems (GES), had become more intentional about teaching metacognition to her students in SCI 100 "Water: An Interdisciplinary Study," a large (600 student), 3-credit course that many non-STEM majors use to meet the lab-science requirement of UMBC's General Education Program (GEP). Specifically, in 2017, she began asking students to "predict" likely midterm and final exam questions—and multiple choice answers—which McGuire suggested in her 2017 UMBC keynote presentation. Working with John Fritz, Associate Vice President for Instructional Technology in Division of Information Technology (DoIT), who taught a 1-credit UMBC orientation and study skills course attached to SCI 100, they found the activity was particularly effective *after* students received their midterm score and were asked to reflect on how their preparation compared to their performance on the exams (Braunschweig & Fritz, 2019).

"Students take SCI 100 to fulfill a graduation distribution requirement," says Braunschweig, who has also worked with UMBC colleagues on helping non-STEM students understand and overcome possible anxieties about science itself (2019a, 2019b). "Inviting them to participate in this metacognition project lets them develop skills that will translate to their other courses. They learn about science by engaging in science!"

In 2023, the SCI100 exam “prediction” and reflection activity was further enhanced after Nancy McAllister, Assistant Teaching Professor of Interdisciplinary Science, suggested using an anonymous Google Form to scale the post-midterm and final exam reflection in all sections. Students completed an LMS-based metacognition tutorial (*Learning and Metacognition Tutorial*, 2023), which was adapted and remixed from Baldwin’s (2023) OpenStax College Success materials. Fritz’ DoIT colleague, Josh Abrams, Instructional Design Specialist, also prototyped a workflow for anonymously gathering and displaying student-generated practice questions and answers for upcoming midterm and final exams, again using Google forms and spreadsheets. Notably, Braunschweig and McAllister also framed the activity as a semester-long extra credit opportunity, which they set up at the beginning of semester. It started with a presentation on Bloom’s Taxonomy of Learning which was reinforced throughout the term.

“Our experience in SCI 100 demonstrates that students engage more deeply with the material when they have a role in shaping their own learning tools,” says McAllister, who has recently received high marks from students about her use of AI-based case studies to redesign a recurring “water journal” reflection assignment (2025). “We look forward to further integrating AI into the course in order to support self-assessment, crowdsource meaningful practice, and foster a culture where students play an active role in shaping their learning journeys.”

Finally, in spring 2024 and influenced greatly by his UMBC Chemistry, GES, INDS faculty and DoIT staff colleagues, Fritz began teaching UNIV 102 “Academic Success Seminar,” a 2-credit study skills course coordinated by the Division of Undergraduate Academic Affairs that is recommended for students who are at risk of academic dismissal due to earning a cumulative grade point average (GPA) below 2.0, and required of students who have been dismissed and are now seeking reinstatement. Typically, UNIV 102 students lack skill in honest and accurate self-assessment about what they currently know, understand or can do, which is essential in learning how to learn. In addition, they are often loners who lack skill and confidence in finding, forming and functioning well in study groups that could (ideally) help develop and reinforce individual members’ self-regulated learning. To help, Fritz introduced the use of Team-based Learning (TBL) to UNIV 102 to see if and how struggling students might gain confidence in self-assessment through team practice in preparation for weekly textbook chapter quizzes. Notably, some of the weekly quiz questions were generated through Google Gemini and a simple prompt to apply Bloom’s Taxonomy for varying levels of learning and rigor.

Findings & Implications

In this section, we briefly describe key findings resulting from or informing each participating course’s actual or potential use of AI to improve students’ metacognition and self-regulated learning. The order is more thematic than chronological, per se, but collectively, we hope to paint a picture of an AI-assisted formative practice ecosystem that incorporates elements of each course’s approach and experience.

CHEM 102 “Principles of Chemistry II”—Scaling “spaced practice” as an alternative to cramming

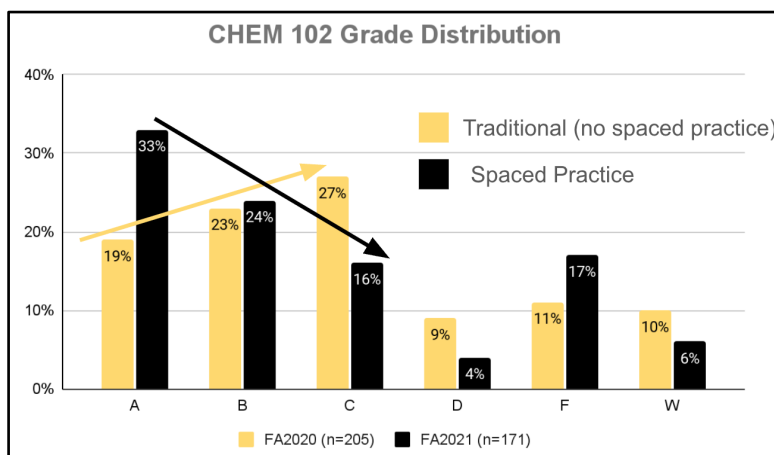
At UMBC, Carpenter has been a long-time champion of spaced practice, a pedagogical approach based on the memory research of German psychologist Herman Ebbinghaus (1885, 2013) who, after memorizing a set of 2,300 random three-letter combinations in a blocked study fashion, found that his immediate ability to recall 100 percent of the letters was reduced to only 60 percent after 19 minutes. Others have replicated his findings (Murre & Dros, 2015), showing that memorized information is lost from the brain exponentially over time (i.e., the forgetting curve). Ebbinghaus also showed that with repeated exposure, the amount of information able to be recalled increased over time (i.e., the learning curve).

As such, spaced practice pedagogy focuses on distributing short, but regular learning sessions over time that enhances long-term retention and promotes deeper learning than “cramming” strategies alone. The effectiveness of spaced practice has been widely confirmed in both simulations and classroom studies in the field of psychology (Burns & Gurung, 2023; S. K. Carpenter, 2020; Dunlosky et al., 2013), and benefits for students have been demonstrated in natural science (Kapler et al., 2015), math (Bego et al., 2024; Gallo & Odu, 2009; Rohrer, 2009), engineering (Hopkins et al., 2016), and introductory physics (Voice & Stirton, 2020).

In her own courses, Carpenter has seen students often bring cramming strategies from high school particularly in CHEM 102 that serves ~800 students a year (typically ~250 in fall and ~550 in spring terms). Notably, she has observed that students who have “opted in” to using her spaced practice approach have not only passed her class with a C or higher (Figure 2), but also the next one, CHEM 351 “Organic Chemistry,” that requires it. Also, the equity of these gains is particularly compelling among students of color (SOC) (2025; 2023b; 2022).

Figure 2

CHEM 102 Grade Distribution Before and After Use of Spaced Practice



However, despite her success, Carpenter and UMBC have encountered both pedagogical and technical challenges to scaling spaced practice further:

- Some students don't take advantage of Carpenter's approach, or even actively resist and undermine it by taking a primarily extrinsic (points) based approach vs. a more intrinsic (learning how they learn) approach. Perhaps even more frustrating, many students who actually want and do use her approach—and say they wanted to do so in future courses—have struggled to author and schedule the practice questions they need if not provided in other courses by design.
- Additionally, to better target and scale her outreach to disengaged or poorly motivated students, Carpenter has changed her technical implementation of spaced practice many times, always with a goal of improving an element of spaced practice principles (e.g., practice question bank development and timing, adaptive or personalized remediation, nudging and messaging, and impact assessment).
- Finally, while many faculty have been impressed with Carpenter's results, some have also been sobered by the manual effort she expends to curate such large practice and exam question banks across different platforms to implement it.

Given these results, Carpenter has explored algorithmically-generated, machine learning approaches in various third-party vended and open-source courseware or publisher supplements to CHEM 102 textbooks. However, the onus of curation and quality-control has largely been her responsibility, if only to scale it in a course as large as hers. As such, key questions and implications for AI include the following, especially for students who pass her course, but find that the next one that requires it does not use spaced practice:

1. If an AI platform could be trusted by faculty subject matter experts, could its use be “delegated” to students, to help generate and schedule their own practice questions?
2. Ideally, could it also adapt to students' demonstrated strengths and weaknesses, so the

formative practice environment is personalized (at scale) to each student's learning needs? To date, we've yet to build or buy such an AI-assisted practice environment, but it is a goal that could help scale an effective pedagogical practice in Carpenter's course as well as those of her colleagues.

Perhaps more importantly, to develop as self-regulated, life-long learners, is there a benefit to student learning in conceptualizing and owning this practice question curation responsibility? With this in mind, we now turn to Braunschweig's and McAllister's semester-long SCI 100 midterm and final exam question "prediction" practice for extra credit.

SCI 100 "Water: An Interdisciplinary Study"—Nudging Students into Self- and Peer-Assessment

From 2022 to 2024, through an internal pedagogical innovation grant, Braunschweig and McAllister refined a flexible, semester-long, extra credit activity designed to develop students' intrinsic motivation to practice and prepare for high-stakes midterm and final exams that faculty will assign any way (2024). Key steps included: (1) introducing students to metacognition based on Bloom's Taxonomy of Learning (Figure 3), per McGuire's suggestion, (2) providing a standardized process for students to anonymously contribute, review and "vote" on the best student-developed practice questions *and* answers, and (3) scaling reflection of their exam preparation vs. performance (especially after a midterm) that can leverage intrinsic motivation to learn how to learn.

Figure 3

"UMBC Learning and Metacognition" Tutorial

Skip to main content

Navigation

- Introduction
- Overview
- Learning Process
- Bloom's Taxonomy
- Applying Bloom's Taxonomy
- Memory
- Study Strategies
- Practice Questions
- How Instructors Design Tests
- Developing Metacognition
- Reflection
- Summary

UMBC

Metacognition
THINKING ABOUT OUR THINKING

Learning and Metacognition

Introduction

This module focuses on your learning, course learning objectives, your thinking and learning processes as a student, and test preparation.

By the time you finish this module, you should be able to do the following:

- Review the learning process and the role of memory in the learning process.
- Identify the cognitive levels of Bloom's taxonomy.
- Explain how the levels of Bloom's taxonomy apply to a course objective, assignment, or test.
- Review effective studying strategies for test preparation.
- Create a plausible test question/answer set based on Bloom's Taxonomy and your knowledge of the course.
- Reflect on your test preparation and test-taking experience after receiving assignment feedback.

This process was implemented in multiple sections of SCI 100 over multiple terms, with compelling results. Specifically, key project findings included the following (credit to DoIT's Tom Penniston, Coordinator for Learning Analytics, for the analysis excerpted below):

- Overall, there's been a decrease in DFW rates in SCI100 sections when comparing Fall 2023 with the past four terms (11.3% vs. 15.9%) and it is statistically significant ($p < .05$).
- Completing only one of the practice exam Q&A activities (i.e., submitting final questions, midterm participation, and final survey completion) boosted students' final grade a minimum of 6.6%, or more than half a letter grade ($\sigma = 12$).
- While the 100 section (control group) of SCI 100 had a slightly lower DFW rate than did the 200 & 300 sections combined (i.e., 5.1% vs. 9.4%) it was not statistically significant.
- There was, however, a discernible, statistically significant difference within the course sections based on testing performance. Specifically, students who increased their test percentage from the midterm to the final demonstrated a 3.6% greater final class average (82.2% vs. 85.8; $p < .05$).

Basically, students could develop their own practice questions and answers, and those who engaged with the exam prediction practice activity performed better compared to peers who did not participate. Indeed, various researchers (Aflalo, 2021; Campenhout et al., 2021; Huang et al., 2021) have also explored the use of student-generated practice questions as a way for students to better prepare for summative exams. Additionally, the University of Michigan's "Problem Roulette" allows students to "study by practicing questions from past exams," albeit submitted by faculty voluntarily. Also, Hodges (2015), McGuire (2015, 2018) and Downing (2010) all reference some form of students—or study groups—being able to anticipate (predict?) questions likely to appear on exams as a key strategy for effective preparation for them.

Still, the incentive structure and workflow to help students find, form and effectively function in student study groups outside of class, especially for extra credit, needs to be refined. For example, consider the following:

- To help standardize the collection, display and study group ranking of student-generated questions, DoIT's Josh Abrams developed a Google Form for collection of student-submitted practice exam Q&A sets.
- Additionally, McCallister decided to use one of her two SCI100 sections (100 students each) as a control group. However, not wanting to deny a potentially effective required assignment to one section, she and Braunschweig agreed to make it an extra credit activity.
- Finally, McCallister, rightly suggested moving to a Google Form survey to gather and analyze student reflections, which was a more scalable approach to the "reflection paper" in SCI100's three, large (~100+) sections she and Braunschweig had taught. From the combined Fall 2023 midterm and final exam reflection survey results in McCallister's (300) and Braunschweig's (200) sections, we learned the following:
 - On average, ~130 students participated in both post-exam surveys.
 - 58% agreed or strongly agreed that "Other students proposed exam Q&A sets helped me prepare for the exam"
 - 65% agreed or strongly agreed that "My perception of my preparation for the exam—before and after I received my actual score—has changed. As a result, I will prepare differently for the next exam"

- 64% agreed or strongly agreed that “My perception of my preparation for the exam—before and after I received my actual score—has changed. As a result, I will prepare differently for the next exam”

Interestingly, if faculty are willing, AI could be prompted to develop multiple choice practice questions based on their own class presentations, handouts, and open educational resources (OER) such as textbooks and notes. In short, by allowing AI to index and summarize their own content, the faculty burden to manually curate their own large practice and exam question banks could be reduced. Of course, with access to the same content, students could do so on their own, if they were to appreciate the value of time on task practice solving problems that help them to “learn by doing.”

UNIV 102 “Academic Success Seminar”—Designing Team Extra Credit for At-Risk Students

Given students’ challenges finding, forming and functioning in student study groups outside of class, Fritz decided to make it an explicit goal in UNIV 102, and centered primarily around student-generated practice questions and multiple-choice answers explored in SCI 100. To do so, he adopted Team-Based Learning (TBL) that often has three main criteria to determine final grades (e.g., individual effort, team effort, and anonymous team peer review). Each semester, students “vote” on specific grade weights within preset minimums and maximums Fritz sets, but typically this results in a final grade weight of ~60 percent individual effort, ~30 percent team effort, and ~10 percent anonymous team peer review.

Fritz also uses the common TBL practice of assigning regular individual and team readiness assurance tests (RATs), in which students take a short, 5-question multiple choice quiz over the assigned readings worth 10 points, but do not get feedback on the correct answers. Then, teams of 4–5 students take the same quiz and are asked to reach consensus on the correct answer, which is identified by a star on a simple, but effective “scratch off” card (*Immediate Feedback Assessment Technique Forms*, n.d.). Teams can also receive partial credit if they eventually arrive at the right answer without using all of them.

Over four consecutive semesters, Fritz—and importantly, the students themselves in each semester—found that teams consistently averaged higher weekly reading quiz scores vs. individuals (typically 99% vs. 62%). This has become a reliable “teaching moment” early in the term, that informs why and how students warm up to a team extra credit activity of coming up with their own practice questions. This in turn leads to a crowd-sourced version for the last chapter quiz Fritz takes sight unseen in front of the entire class, which they love, as a chance to “turn the tables on the prof.”

In spring 2025, beyond using Google Gemini to supplement the UNIV 102 textbook’s delivered question banks for the weekly chapter quizzes, Fritz also used AI in the following ways:

- Developed a “True Grit” (UMBC’s mascot) “Role Play” using the delivered AI Conversation functionality in the campus’ Blackboard learning management system (LMS) (Anthology, n.d.). In this scenario, students are asked to pretend they are the TA for UNIV 102, and tasked with drafting the weekly chapter quiz questions AND answers

based on the textbook and using a different level of Bloom's taxonomy as the rigor or level of learning to be assessed. Alas, it was introduced after the semester had started, and only two students used it, but it has potential for helping students jump-start wearing another hat in the service of their own self-regulated learning.

- For fall 2025, Fritz has also created a Google Gemini “Gem” to prompt and develop a student demo (Figure 4) and faculty guide for how to implement his “Team Extra Credit” activity (Fritz, 2025). There are still a few custom integrations he would have to develop to create a stand-alone site, but the workflow is tighter and could potentially be turned into a Google Assignment any faculty member could use for extra credit that, more often than not, is simply bolted on at the end of a term anyway.

Figure 4

UNIV 102 Student Demo of Crowdsourced Study Guide Developed in Google Gemini

Crowdsourced Study Guide Preview					
Below is a live preview of the anonymized study guide that students will see. It's designed for easy review and collaboration. Use the buttons to test the sorting functionality that helps students focus their study efforts.					
Sort by Question Ranking Sort by Chapter Sort by Bloom's Level Sort by Team					
RANKING	CHAPTER	TEAM	BLOOM'S	PRACTICE QUESTION	EXPLANATION SNIPPET
31	3	3	Evaluate	Which strategy would be most effective for a student with low course value?	Connecting course content to their personal goals or dream life...
22	3	2	Understand	Which of the following best explains the concept of "Victim Mindset"?	It involves believing external forces determine your fate...
18	2	5	Analyze	How does personal responsibility relate to the "Creator Mindset"?	Creators accept responsibility as the foundation for making choices...

CHEM 101 “Principles of Chemistry I”—Creating a 24/7 Virtual Prof to Answer Student Q&As

While student study groups can help formative practice for exams, they also need just-in-time subject matter expertise. But instructors can't provide 24/7 support. Also, open-ended practice is great but hard to scale. Facing these long-standing logistical and pedagogical challenges, Sarah Bass, Associate Teaching Professor of Chemistry, essentially decided to clone herself through the following prompt to UMBC's Google's NotebookLM environment (Bass et al., 2025):

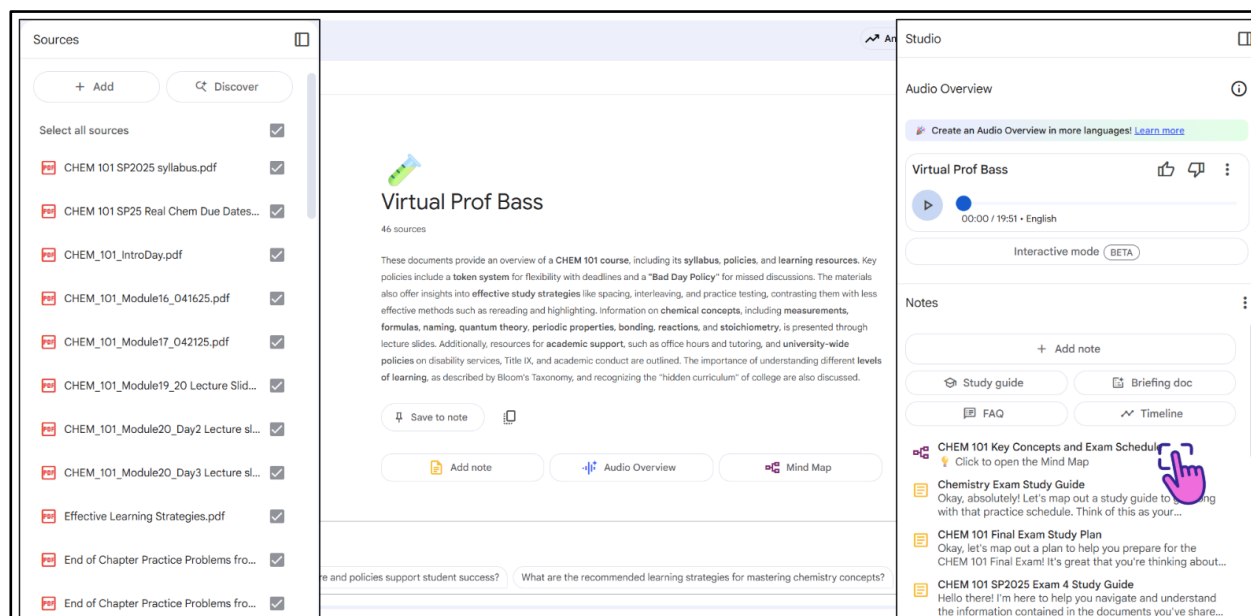
You are a friendly, supportive chemistry instructor focused on guiding students to discover answers independently. Acknowledge their effort, ask guiding questions, and

encourage recall of relevant concepts. Prompt students to explain their reasoning and help clarify misunderstandings. If needed, offer subtle hints or reminders of key concepts. Only provide course resource references for logistics-related questions. Maintain a patient, encouraging tone and keep answers concise.

Bass introduced and demonstrated the resulting “Virtual Prof Bass” (Figure 5) in class, on Monday, April 14, 2025, just before exam 3, accompanied by a palpable buzz from more than 300 students in attendance. Among other things, they saw Bass demo a chat interface that correctly and empathetically answered any question she posed based on the 36 handouts, presentations and notes she’d created for CHEM 101. There are several spaced practice inspired study guides, a concept map of all course topics and even interactive podcasts by two AI “hosts” who take and answer student questions verbally.

Figure 5

Virtual Prof Bass Google NotebookLM



At the end of the spring 2025 semester, Bass presented her experience of a faculty panel on the use of AI in formative practice (2025) and then as a stand-alone presentation the next semester (Bass, 2025). She also surveyed students about the “Virtual Prof Bass” NotebookLM and received both constructive and encouraging feedback she is incorporating into a revised version for her much larger CHEM 101 course in fall 2025. Excerpts include the following:

- I really like the way the chat response pulls information directly from the course content and directs you exactly where to look...
- When you click on a key topic, it gives you the pertinent information in the chat window, as well as directing you to the correct unit slides for review.
- The study guide is great!
- The quiz at the end of the study guide is a nice addition.

- My favorite part is the interactive chat. I like that I can ask for clarification on a topic and not only get a brief response but also the information for where to find additional information.
- Overall, I like it

“The key takeaway for me is that students are already using AI, but lack skill in how to use it effectively,” says Bass, who will continue researching the impact of her 24/7 cloned self through a learning analytics mini-grant aimed at extracting students’ NotebookLM usage data to correlate with exam and final grades earned. “With AI, we’re not replacing teaching, we’re expanding it.”

Discussion

In these four courses, we’ve learned what the elements of an ideal and actual AI-assisted personal learning environment might look like to help students become more self-regulated learners. For example, consider the following:

- CHEM 102 “Principles of Chemistry II”—[Spaced] Practice makes perfect, but students struggle to understand why and how they can and should take on the responsibility for learning throughout all of their courses. Additionally, faculty may need help and guidance to bend AI toward their will to do so. Hint: Start with AI-generated question banks and distributed practice plan.
- SCI 100 “Water: An Interdisciplinary Study”—Students can and do learn how to ask and answer formative practice questions, but this is not a typical role they encounter in all of their courses. It may take a teachable moment (e.g., reflecting on one’s preparation vs. performance after a disappointing midterm exam) to motivate them to do so. Additionally, designing a workflow that helps is challenging for faculty using readily available tools that could scale the approach for their colleagues and peers.
- UNIV 102: “Academic Success Seminar”—Helping struggling students find, form and function in student study groups outside of class may not occur without direct intervention within a course—by design. Also, AI could help model and assist how to ask and answer formative practice questions, but a weekly reality check in the form of low stakes individual vs. team chapter reading quiz could help keep them on track.
- CHEM 101 “Principles of Chemistry I”—Creating an AI agent is possible and students find value in extending the availability and (importantly) tone of an instructor in a large, gateway STEM course. However, they may need to be prepped early and often throughout the term, to understand why and how they should do so to supplement and take responsibility for their own learning.

Conclusion

Inevitably, as with any new disruptive technology (e.g., the internet, Wikipedia, smartphones, etc.), we may be seeing a leveling off of the “moral angst” argument about students cheating with AI. Instead, we hope to see a more balanced exploration and discussion of what’s

possible with AI to facilitate or even deepen students' willingness and ability to honestly and accurately assess what they currently know, understand or can do.

Indeed, a recent study reported in *Harvard Business Review* concluded that the mixed results from employee use of AI to increase productivity was correlated to those who “monitor” their thinking vs. those who do not (Lu et al., 2026). That said, other studies (Gerlich, 2025; Handa et al., 2025; Oakley et al., 2025) and commentary (Kellen, 2025; McMurtrie, 2025) have emerged about how the use of AI can lead to “cognitive offloading” of higher order thinking (e.g., analysis, evaluation, even creation per Bloom’s Taxonomy).

Perhaps now more than ever, as McGuire rightly suggests, we need to equip students with explicit instruction in and appreciation for metacognition and thinking about their own thinking and learning how to learn. Coupled with the benefits of learning from and appreciating others, AI-assisted personal learning environments could help scale self-assessment as an instinct and habit of mind to become a lifelong, self-regulated learner as well as a collaborative, productive member of society.

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The Promise and Paradox of AI in Doctoral Education

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Abstract

This paper proposes a conceptual model of adaptive artificial intelligence (AI) support for doctoral education that operationalizes supported autonomy across three interconnected dimensions of doctoral student development: cognitive, affective, and social. Each dimension represents a distinct but overlapping area where AI can provide responsive scaffolding while preserving student agency and intellectual ownership. This framework provides a structured approach to understanding how AI tools can enhance rather than diminish doctoral development when thoughtfully integrated into mentorship and supervision structures. Challenges and ethical use are addressed along with implications for doctoral programs. We suggest a balanced use of AI, a clear framework or guidelines for ethical use, and doctoral student supervision (dissertation chair) to reduce feelings of isolation, student attrition, and use of students' time.

Keywords: Adaptive artificial intelligence (AI), support for doctoral students, doctoral programs, artificial intelligence and doctoral education, doctoral student attrition, online doctoral programs

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Traditionally, doctoral education programs have been grounded in the idea of an independent scholar and researcher who demonstrates autonomy and mastery through largely solitary work during the dissertation phase. However, this model often leads to isolation and, at times, stagnation, particularly since structured coursework and faculty contact are often diminished (Ali & Kohun, 2007; Rockinson-Szapkiw et al., 2014; Wegener et al., 2016). Because of unstructured format and periods of isolation, doctoral student attrition rates are high and concerning (Breitenbach, 2023; Wegener et al., 2016; Young, 2019).

However, the emerging paradigm of the AI-augmented scholar redefines student independence as supporting autonomy or maintaining intellectual ownership while leveraging AI to scaffold critical aspects of the research and writing process. In this new model, generative AI functions as a dynamic, adaptive support system rather than a static writing aid. Artificial intelligence (AI) provides immediate, context-sensitive feedback (Tensen et al., 2025), helps overcome cognitive bottlenecks such as writer's block or imposter syndrome (Chakraverty, 2019), and fosters reflective learning rather than rote automation (Holmes et al., 2019; Kasneci et al., 2023), all of which can greatly enhance a doctoral program (Migliore, 2024). Doctoral programs that integrate the use of AI can enrich the student educational journey while also better preparing them for necessary future professional skills such as decision making, strategic thinking, and ethical considerations (Migliore, 2024).

The purpose of this article is to introduce an AI-augmented scholar framework. This framework positions AI as a doctoral student's critical friend in conjunction with human mentorship. Between AI and doctoral advisors, students will be better prepared to avoid isolation and persist through research while maintaining momentum and confidence throughout the dissertation process.

From Manual to Augmented Scholarship

Before the early 2000s, academic research was primarily a time-intensive and manual endeavor. Scholars at all stages, especially those in the early phases of their careers, relied on physical libraries, printed indexes, and institutional access to locate and synthesize information. Even though some artificial intelligence tools (machine learning) did exist, they were still in their infancy. Locating relevant scholarship required hours of consulting card catalogs, journal indices, and paper-based bibliographies, and access to the knowledge needed for research was often constrained by geographic and institutional boundaries. These barriers not only limited efficiency but also reinforced disparities in scholarly opportunity and pace of discovery.

The turn of the millennium marked a pivotal transformation with the widespread adoption of the internet and digital databases. The digitization of journals and the emergence of online repositories such as JSTOR (1995), PubMed (1996), and Google Scholar (2004) have revolutionized information accessibility (Jacso, 2005). This digital revolution democratized research by allowing scholars to retrieve and cross-reference materials almost instantaneously.

The median number of databases consulted by researchers rose from one in 1994 to four in 2014 (Lam & McDiarmid, 2016), illustrating how digital tools expanded both the speed and scope of inquiry. For the first time, access to knowledge became less dependent on institutions

providing access and more on digital connectivity.

As digital infrastructure matured, scholarship evolved beyond information retrieval toward collaboration and openness. The open access movement, galvanized by the Budapest Open Access Initiative (2001), promoted the free exchange of ideas and dismantled paywalls that restricted participation in global knowledge production (Suber, 2012). Platforms such as Academia.edu and ResearchGate enabled researchers to share preprints, collaborate across disciplines, and build professional networks that blurred traditional institutional boundaries (Jordan, 2019). These developments shaped what Weller (2011) termed as the “digital scholar”: a model in which online engagement, data sharing, and public scholarship became central to academic identity and productivity.

The current wave of AI integration represents the next evolutionary stage in this continuum. While the Internet expands access to knowledge, AI extends interpretive and generative knowledge capacity (Liu & Jagadish, 2024). Emerging tools powered by large language models (LLMs) and machine learning now support literature synthesis, data analysis, and the generation of research hypotheses. These technologies signal a shift from digital scholarship to augmented scholarship, in which AI functions not merely as an information-retrieval mechanism but as an adaptive partner in reasoning, writing, and discovery (Holmes et al., 2019; Kasneci et al., 2023; Liu & Jagadish, 2024).

For the AI-augmented scholar, these developments offer adaptive and continuous support in the research process. Just as digitization provided increased access to information, AI now provides tools for scaffolding by providing real-time, personalized assistance that enhances how scholars think, write, and learn (Lin et al., 2023). This shift sets the stage for understanding how doctoral students can leverage AI tools not only to increase efficiency but also to cultivate autonomy, confidence, and persistence within the dissertation process.

AI Support Tools for Doctoral Student Research

The use of AI in higher education has rapidly increased with the emergence of generative AI (GAI) tools using large language models (LLMs) such as OpenAI’s ChatGPT and Google’s basis (Rong & Chung, 2024). Despite both students and faculty being initially suspicious of AI usage, doctoral students are now finding AI tools particularly helpful in academic writing, which, to complete their degree, doctoral students must grasp. Many AI tools now support and enhance the dissertation process by helping with topic suggestions, locating recent or related research, creating outlines, writing and editing a literature review, analyzing data collected for their research, and even aiding in the presentation of the findings. In fact, one empirical study found that ChatGPT improves the doctoral experience by performing automated tasks, saving time by simplifying research, and alleviating stress and cognitive load (Ringo, 2024).

In addition, Oliinyk et al. (2024) found that AI can contribute to the improvement of research competencies needed for dissertation research, with AI tools providing access to academic databases and suggesting related journal articles and relevant datasets (Omodan, 2025). This kind of access saves time and allows doctoral students to focus on the more critical areas of the research study (Boyd & Harding, 2025; Lesh & Lancaster, 2024). Moreover, Li and Lin

(2025) showed that doctoral students appreciated the personalized instant feedback, further saving them time. While students must not depend solely on AI tools to complete their research, these emerging AI tools can offer non-judgmental, early-stage support to prepare for meetings with supervisors.

Currently, there are a plethora of AI tools available to doctoral students, many of them free to use while others charge different fees for levels of access. We provide just a small list of potential specific AI tools doctoral students are using or could use to assist with their research; of course, the large language models such as *ChatGPT*, *Gemini*, *Claude*, *CoPilot* and others may also be used. We acknowledge there are many more tools available.

Literature Review and Writing

Many AI tools can assist with better literature review development by identifying, summarizing, and synthesizing scholarly literature (Fabiano et al., 2024). In fact, Bista and Bista (2025) recently found that doctoral students had improved clarity in their writing when using AI support while Nguyen et al. (2023) saw increased performance in writing tasks. Buss et al. (2025) asserted that doctoral students had more confidence using AI tools when the instructors introduced it as an option. However, doctoral students should be taught [and reminded] to cross-verify any information used and the importance of human oversight (Fabiano et al., 2024).

Many tools are available for searching and supporting the literature review. For example, *Elicit* assists doctoral students in finding, summarizing, and extracting key information from academic articles, and *Research Rabbit* offers visual mapping of article collections. Article summaries provided by tools like *SciSummary* and *Semantic Scholar* can save students a lot of time from having to read articles that do not really match the research. *Iris.AI* takes a more visual approach by analyzing research papers and generating concept maps, while *Liner Scholar AI* specializes in literature review comparisons and writing and offers hypothesis and survey generation capabilities. Similarly, *Undermind AI* supports targeted literature searches and helps refine research questions. *Trinka AI* provides specialized proofreading for grammar and spelling mistakes tailored to academic writing.

For more accurate citations, *Scite AI* provides comprehensive searches over 1.5 billion citations, connecting supporting research and enabling citation checking and cross-referencing through Smart Citations. *Scholar AI* complements this process by searching relevant information, generating citations, and extracting data from figures and tables within articles. *Consensus AI* assists doctoral students with searching and analyzing peer-reviewed literature, while *AskYourPDF* facilitates chatting with, summarizing, and extracting information from PDF-formatted research articles. *SciSpace* offers comprehensive support, including deeper literature review capabilities, and provides article summaries and writing assistance.

Data Analysis

Dissertation data analysis can be improved with the use of AI tools. For example, researchers working with qualitative data can use robust platforms that offer transcription and analysis capabilities. *NVivo* and *ATLAS.ti* both provide transcription and qualitative data analysis functions, while *MAXQDA* also offers data coding, organization, and presentation assistance. For researchers working with quantitative data, the most common tools already being used, such as

SPSS and *SAS*, are now much more enhanced by AI to assist with data preparation and pattern detection. Additional tools include *Tableau*, which uses AI-powered features like "Ask Data" for natural language queries and automated insight generation from datasets, and *Power BI* (Microsoft), which incorporates AI visuals and intelligent data discovery.

While we provided a very small list of tools, many others offer doctoral students immediate, on-demand support that better adapt to students' schedules. Dissertation work rarely happens during traditional business hours when faculty may be less available due to their own research travels or reduced institutional presence.

AI's availability does not diminish the importance of supervisor mentorship; rather, it makes that mentorship more effective by ensuring students arrive at supervisor meetings with more developed questions, clearer drafts, and more focused needs (Krumsvik, 2025; Tensen et al., 2025). Instead of spending face-to-face time on preliminary feedback that AI could provide ("this paragraph is unclear" or "you need more evidence for this claim"), supervisors can focus on higher-order guidance that requires disciplinary expertise, career mentorship, and scholarly relationships that have been nurtured and sustained by human interaction.

A Framework for Adaptive and Continuous Support

In many doctoral programs, the dissertation phase traditionally becomes a primarily independent endeavor. Students often take classes together in cohorts, forming bonds and experiencing success and struggle collectively. Then there is a clear shift from the excitement of beginning research to the sudden realization there are periods of isolation in the research and writing phase. This abrupt transition from structured, socially connected coursework to solitary dissertation work has long been identified as a critical juncture where many students falter due to the disappearance of support structures precisely when the work becomes most challenging (Carter-Veale et al., 2016; Lovitts, 2008; Mensah, 2025).

However, we suggest the isolation of the dissertation phase can be improved if we redefine independence itself as supported autonomy. Supported autonomy in doctoral education refers to students' capacity to independently direct their research while strategically leveraging appropriate support structures (Jameson et al., 2023). It reconceptualizes independence as the ability to identify needs, critically evaluate resources, and maintain intellectual ownership while engaging productively with supervisors, peers, tools, and technologies (Choi et al., 2021). True autonomy emerges from knowing when and how to seek support, while supported autonomy utilizes various sources to gain needed support.

This reframing coincides with how the dissertation process works as a distributed, collaborative enterprise where success depends on effectively orchestrating resources rather than working in isolation. As Aitchison and Mowbray (2015) argued, the myth of the solitary doctoral scholar obscures the reality that all successful academics strategically mobilize various forms of support, from peer feedback to writing groups to editorial assistance. Supported autonomy makes this reality explicit and positions it as a legitimate and essential part of doctoral student development.

Theoretical Foundation: Vygotsky's Sociocultural Learning

Vygotsky (1978) offered a theoretical foundation for understanding supported autonomy through three interconnected concepts: socially mediated learning, the zone of proximal development (ZPD), and scaffolding. His Sociocultural Learning framework challenges the myth of isolated knowledge construction, positioning all learning, including advanced doctoral work, as inherently social and tool mediated. Learning, in this view, is not merely an individual cognitive process but emerges through interaction with more knowledgeable others, cultural tools (including language and technology), and social contexts that shape what and how we come to know.

The ZPD, defined as the distance between what learners can do independently and what they can accomplish with appropriate support, directly applies to the dissertation phase (Morton et al., 2014). Doctoral students develop expertise in areas where they are not yet fully independent scholars such as designing original studies, synthesizing academic literature, contributing novel theoretical insights, and mastering the discourse conventions of their disciplines. The dissertation represents work at the edge of students' current capabilities, squarely within their ZPD. Without appropriate scaffolding to bridge the gap between current and desired competence, students may struggle unnecessarily or fail to reach their potential (Morton et al., 2014).

Scaffolding, temporary support structures that are gradually removed as competence develops, provides the mechanism for moving students through their ZPD toward genuine independence. Critically, effective scaffolding is adaptive and responsive by providing maximum support when learners need it most and fades systematically as learners internalize skills and strategies (Taber, 2018). In doctoral education, scaffolding has traditionally come from supervisors, coursework, writing centers, and peer networks (Liechty et al., 2009). However, these supports are often inconsistently available, particularly during the dissertation phase when formal structures recede but student needs remain acute. This creates what we might call a “scaffolding gap” or a mismatch between the support students need and the support available to them.

AI Supporting Autonomy in Practice: Bridging the Scaffolding Gap

In our work with doctoral students, we have observed that learning and growth flourish in carefully designed social contexts that bridge the scaffolding gap between coursework and dissertation. Collaborative writing circles exemplify this principle: students gather regularly to share drafts, ask questions, and provide peer feedback in facilitated sessions. These circles serve multiple functions simultaneously. They build confidence through helping others, as students discover they have valuable insights to offer even while struggling with their own work (Tyndall et al., 2019). They also normalize the struggle of academic writing, countering the imposter syndrome that thrives in isolation (Bravata et al., 2019; Craddock et al., 2011; Wang & Li, 2023) when students assume everyone else finds the process easier. Writing circles also create accountability structures that counter the drift and procrastination that can emerge without external deadlines. In addition, they provide regular, low-stakes opportunities for students to practice articulating their ideas and responding to questions, essential skills for navigating defenses and peer review.

Moreover, writing circles bridge the transition from faculty-guided coursework to self-directed research by providing a “middle space” where students can test ideas, receive feedback, and develop their scholarly voice in a lower-stakes environment than formal supervisor meetings or conference presentations (Tyndall et al., 2019). This transition space aligns with Vygotsky's (1978) concept of the ZPD as peers and facilitators provide just enough support to help students accomplish what they cannot yet do entirely alone—revise a confusing paragraph, identify gaps in an argument, or gain perspective on a methodological dilemma—while leaving intellectual ownership firmly in student hands. Over time, students internalize the questioning strategies and feedback approaches modeled in these sessions, gradually needing less external support as they develop more sophisticated self-monitoring capabilities.

Scaffolding is particularly important for students navigating the dissertation process. Typically, the student's first encounter at dissertation stage involves tackling challenges with topic selection, creating an original research design, developing an extended argument, and managing ambiguity over years that at times have no direct connection to coursework. While doctoral coursework provides essential scaffolding through structured assignments, regular deadlines, and immediate faculty presence, this support often dissipates abruptly at the dissertation stage. Students who thrived with weekly seminars and frequent feedback suddenly find themselves working in relative isolation, expected to self-regulate over months or years with only occasional supervisor check-ins. The scaffolding gap created by this transition is especially pronounced for students who lack strong external support networks, including part-time students balancing work and family obligations, international students far from home support systems, and first-generation doctoral students without family models of extended academic work. Pittaway et al. (2023) recommends that scaffolding support should focus on dissertation students completing smaller tasks and then moving to larger tasks during the research process; we believe the use of artificial intelligent tools can provide that kind of incremental support.

AI as Complementing Human Mentorship

The scaffolding gap also creates an opening for AI tools to complement traditional mentorship structures in meaningful ways. Students may hesitate to reveal uncertainty or confusion to faculty advisors, particularly given the power dynamics at play in the supervisor-student relationship (Lovitts, 2001), or if they are legitimately concerned about appearing incompetent or unprepared. The dissertation phase increases students' vulnerability by requiring them to engage in writing and research in new ways. In this context, AI can serve as a “first responder” for half-formed ideas, initial draft feedback, or methodological questions, allowing students to refine their thinking before engaging supervisors (Tensen et al., 2025). This parallel resembles how students might rehearse a difficult conversation with a friend before approaching a supervisor or how they might revise a draft multiple times before sharing it. AI simply provides another tool for this preparatory work.

Moreover, AI can provide adaptive scaffolding that responds to individual student development (Vygotsky, 1978). A student early in the dissertation process might use AI to generate initial literature search terms, understand methodological options, or create preliminary outlines, relatively direct support for foundational work. As the same student progresses, AI use might shift to more Socratic functions: asking the student to justify theoretical choices, identify

limitations in their arguments, or consider alternative interpretations of data. This progression mirrors effective human mentorship, which adapts from more directive guidance for novices to increasingly questioning and challenging stances as students develop expertise. The key difference is that AI can provide this responsiveness at scale and on demand in ways that individual supervisors, however dedicated, cannot match, given their finite time and multiple competing responsibilities.

Conceptualizing Supported Autonomy

Supported autonomy is a fundamentally different way of understanding what independence means in doctoral education. In this framework, autonomy is demonstrated not by students working in isolation, but by:

- **Making informed decisions about research direction and methodology.** Students exercise intellectual independence when they can articulate why they chose specific theoretical frameworks, research designs, or analytical approaches because they critically evaluated options and made strategic choices aligned with their research questions and epistemological commitments (Creswell & Creswell, 2023).
- **Critically evaluating feedback and resources from multiple sources (human and technological).** Rather than accepting all input, autonomous scholars develop the capacity to weigh feedback and advice from generative AI tools (Shulman, 1991). It is important to recognize when feedback reflects genuine limitations in their work and make principled decisions about what to incorporate and what to set aside.
- **Strategically deploying available scaffolds (supervisors, peers, AI tools, literature) to advance scholarly goals.** Independence includes recognizing when additional perspectives would strengthen the work and actively seeking appropriate support (Zimmerman, 2002). This might mean bringing a statistical question to a methodologist, asking a writing center consultant to review argument flow, or using AI to generate alternative phrasings of a complex idea (Pintrich, 2000).
- **Gradually internalizing supported processes to reduce dependence over time.** Effective scaffolding is designed to fade (Vygotsky, 1978). Students who initially rely heavily on external feedback from supervisors, peers, or AI should progressively develop more sophisticated self-monitoring and self-evaluation capabilities (Zimmerman, 2002). The goal is not permanent dependence on any support structure but rather the development of internalized questioning and revision practices (Pintrich, 2000).
- **Maintaining ownership of intellectual work while acknowledging the distributed nature of knowledge production.** Supported autonomy requires students to remain the primary decision-makers and authors of their work even while receiving substantial input from others (Hutchins, 1995). This means clearly distinguishing between using AI to explore ideas versus allowing AI to generate ideas and between receiving feedback on drafts versus having others substantially rewrite the work (Miao & Holmes, 2023).

Supported autonomy shifts the measure of doctoral success from “How much did you do

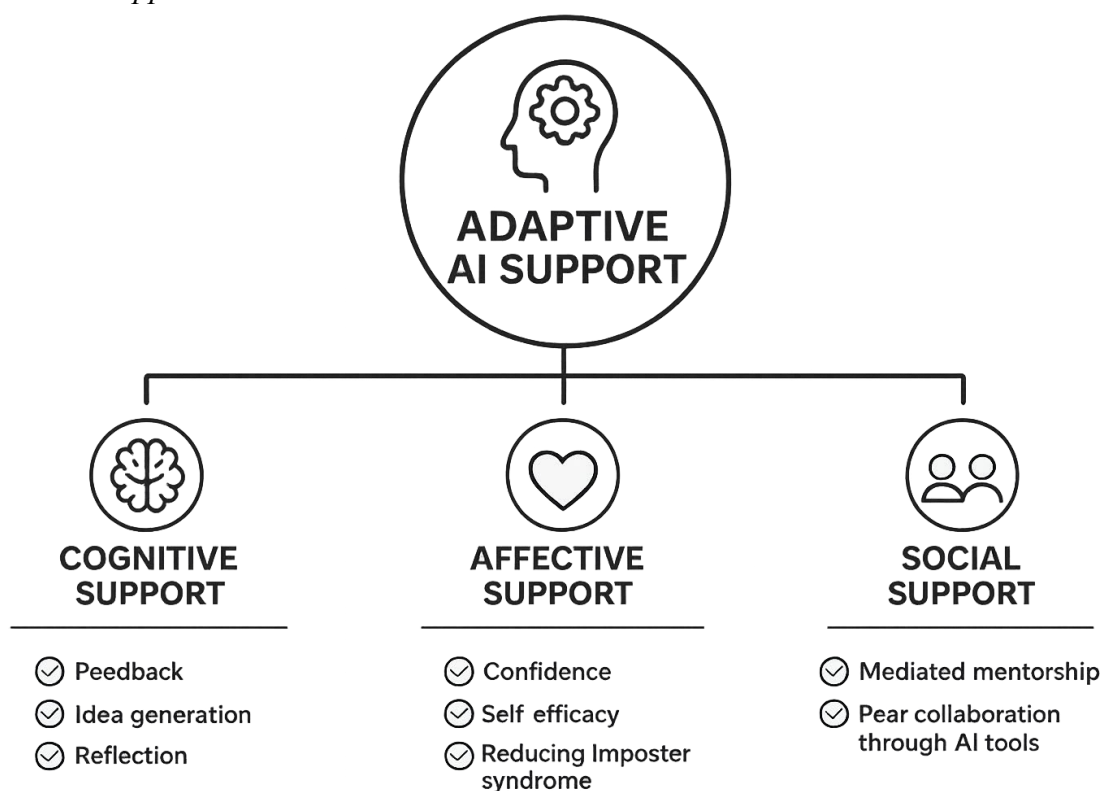
alone?” to “How effectively did you orchestrate resources to produce original, rigorous scholarship while developing transferable capacities for independent inquiry?” This reframing has profound implications for how we design doctoral programs, train supervisors, and integrate emerging technologies like AI into the dissertation process. Rather than viewing AI tools with suspicion as potential threats to academic integrity or student development, we can ask: How might these tools be integrated as adaptive scaffolds that support the development of genuine scholarly autonomy?

Conceptual Model of Adaptive AI Support for Doctoral Education

To answer this question, we propose an adaptive AI support framework that operationalizes supported autonomy across three interconnected dimensions of doctoral student development: cognitive, affective, and social. Each dimension represents a distinct but overlapping area where AI can provide responsive scaffolding while preserving student agency and intellectual ownership. This framework provides a structured approach to understanding how AI tools can enhance rather than diminish doctoral development when thoughtfully integrated into mentorship and supervision structures.

Figure 1

Adaptive AI Support



Note: Figure generated by ChatGPT AI using the proposed dimensions of the conceptual model.

Cognitive Support

Within the adaptive AI support framework, cognitive support addresses the intellectual scaffolding students require as they navigate the complex demands of dissertation research (Ge, 2010). AI tools, when integrated alongside faculty and peer support, can fundamentally reshape how students receive and comprehend research guidance throughout the dissertation process. Doctoral students frequently encounter obstacles at various phases of their work: clarifying theoretical frameworks, designing methodological approaches, synthesizing literature, or structuring arguments (Bista & Bista, 2025). Quality and timely feedback proves instrumental in helping students move through these challenges (Nicol & Macfarlane-Dick, 2006). Faculty dissertation chairs should ideally provide substantive and regular feedback to support student progress (Burrington et al., 2022). However, the realities of contemporary doctoral education often create significant delays. The number of doctoral students requiring supervision, combined with grading responsibilities and other institutional obligations, means that feedback loops can stretch across weeks or even months (Gardner, 2009). This lag frustrates students who may misunderstand advisor schedules or availability, leading to stalled progress and mounting anxiety.

The supervisory relationship should cultivate space for idea generation and deep reflection, creating an iterative loop that enables students to question their own assumptions, refine research strategies, and develop more sophisticated analytical frameworks (Welsh & Dehler., 2013). When students need a conceptual push, faculty members can serve as thought partners, helping brainstorm alternatives or reframe problems. However, competing demands on faculty time may delay these supportive interactions, leaving students waiting for guidance at critical junctures in the research process.

AI offers a complementary form of cognitive support that addresses the time constraints of traditional mentorship. Functioning as an “always-available” critical friend, AI may strengthen credibility, transferability, and dependability by prompting analytic reflexivity and structural clarity, but responsibility for establishing trustworthiness remains with the researcher (Hutchins, 1995; Lincoln, & Guba, 1985). This constant availability of support is especially valuable when supervisor feedback may be delayed due to workload or scheduling conflicts. Students can use AI tools to refine their thinking and then share these ideas with faculty, keeping advisors informed while maintaining progress between formal meetings.

Generative AI also supports brainstorming for research questions, theoretical frameworks, and methodological approaches, helping students move beyond writer's block or the paralysis of confronting a blank page. The technology can prompt students to reflect on and question their own assertions and connections, providing a valuable metacognitive check for those who may feel hesitant to reveal confusion or gaps in understanding to their advisors (Welsh & Dehler, 2013).

AI can provide cognitive scaffolding in ways that complement rather than replace human expertise. Students who use AI to work through preliminary questions or test early drafts arrive at advisor meetings better prepared, with more focused inquiries and clearer articulation of their challenges. This efficient preparation can enhance the quality of faculty-student interactions by ensuring that limited face-to-face time addresses higher-order concerns requiring disciplinary

expertise rather than preliminary feedback AI can readily provide. Faculty members remain essential to the process, but AI can help optimize when and how their expertise is deployed.

The adaptive nature of AI support allows it to calibrate intensity based on student needs (Vygotsky, 1978) and departmental values. For instance, chatbots can be trained to emphasize Socratic questioning methods that encourage student reflection rather than providing directive answers. Early-stage researchers might receive more structured prompts that help them understand conventions of literature reviews or research design, while advanced students encounter more challenging questions that push them to justify theoretical choices or consider alternative interpretations of their findings. Faculty oversight remains critical in establishing these parameters, ensuring that AI tools align with program pedagogies and disciplinary norms (Nicol & Macfarlane-Dick, 2006). This adaptive element enables AI to provide timely cognitive support while respecting the intellectual authority and ethical guidelines faculty must maintain. By offering responsive, immediate feedback that bridges the gaps between advisor meetings, AI cognitive support can enhance doctoral student persistence while simultaneously reducing some of the mentorship burden that contributes to faculty overload. The goal is not to replace the irreplaceable elements of human mentorship but to create a more sustainable support ecosystem where technology handles routine cognitive scaffolding, freeing faculty to focus on the nuanced, discipline-specific, and relational dimensions of doctoral education that only human mentors can provide.

Affective Support

Cognitive scaffolding supports the intellectual side of dissertation work, while affective support focuses on the emotional and psychological factors that shape whether doctoral students persist and succeed. The dissertation stage can pose academic challenges and threaten students' confidence. Studies show that the emotional strain of doctoral work is a key reason for student dropout and affects overall well-being (Sverdlik et al., 2018). Imposter syndrome often worsens during the dissertation phase, when students typically work alone and without the familiar structures of the classroom (Bravata et al., 2019; Wang & Li, 2023).

Affective challenges in doctoral work may come from how vulnerable the process can feel. Sharing unfinished work for feedback is daunting because it requires students to confront their limits and expose their insecurities (Lovitts, 2001; King & Kitchener, 1994). These vulnerabilities can help or erode students' confidence; this is especially true for students from historically underrepresented groups who may already feel out of place in academic settings (Stubb et al., 2011). Without adequate emotional support, students may shy away from seeking feedback, missing the opportunity to strengthen their work.

AI tools can provide students with a safe space to try out ideas without worrying about being judged. AI provides a low-pressure environment for testing out concepts, building arguments, or expressing confusion. Students can ask simple questions, rewrite the same paragraph as many times as they need to, or explore side ideas without feeling they are wasting time or showing weakness. While supervisors provide disciplinary judgment and expert feedback, AI offers 24/7 drafting support and a non-judgmental platform. This kind of safety encourages students to take risks and practice, which helps them build much-needed skills.

Generative AI can also help students recognize that struggling with dissertation work is normal and build confidence by allowing them to achieve small, manageable goals (Bandura, 1997). By breaking big dissertation tasks into smaller steps with AI support, students enjoy consistent small successes that, cumulatively, give students the confidence to take on bigger challenges. Over time, they build a record of solving problems, which negates the idea that success is just about luck (Clance & Imes, 1978).

Affective AI support can adjust its encouragement and challenges to fit students' needs. At the start of the dissertation, AI may provide more positive feedback to help students feel confident and less anxious. As students improve, AI can continue to be supportive while also asking tougher questions to help them think more deeply. This approach resembles human mentoring with consistent access since AI is always available (Sverdlik et al., 2018).

Social Support

Beyond cognitive and affective dimensions, doctoral success also depends on social support structures that connect students to mentors and peers (Anttila et al., 2024; Rockinson-Szapkiw et al., 2014). Doctoral education is inherently relational, despite the persistent narrative of solitary scholarship (Dysthe et al., 2006). Students develop scholarly identities through ongoing interactions with advisors, peers, and intentional academic networks that situate their work within larger conversations. The dissertation phase, however, often disrupts these social connections precisely when students need them most. Coursework cohorts may disappear when students begin pursuing their research projects. As a result, face-to-face interactions with supervisors become less frequent, and extended periods of independent work can leave students feeling disconnected (Ciampa & Wolfe, 2023).

This social isolation has significant consequences for persistence and learning. One study found that doctoral students with strong relationships within their academic communities have greater control over their work, are happier, and complete their degrees more quickly (Vekkaila et al., 2018). Conversely, social isolation correlates with increased attrition, diminished well-being, and slower progress (Ali & Kohun, 2007; Mensah, 2025). Students need regular opportunities to articulate their emerging ideas, receive varied perspectives, and experience themselves as legitimate participants in scholarly discourse. Supervision alone cannot meet all these social needs, particularly given the power dynamics and evaluation pressures inherent in advisor-student relationships (Manathunga, 2007).

AI tools offer novel approaches to augmenting rather than replacing the social dimensions of doctoral education. Rather than substituting for human connection, AI can enhance the quality and efficiency of mentorship relationships by serving as a “first responder” that helps students refine questions and drafts before supervisor meetings. Students can use AI to clarify their thinking, identify gaps in arguments, or explore preliminary ideas before bringing more developed work to advisors. This preparation makes limited face-to-face time more productive, allowing supervisors to focus on higher-order guidance that requires disciplinary expertise and relational knowledge rather than preliminary feedback. The results create more substantive and satisfying mentorship exchanges, rather than reducing human interaction. AI support becomes especially valuable as it provides a form of connection that bridges geographical, temporal, and social distances, offering always-available interaction when human

networks prove inaccessible (Martinez, 2024).

The concept of mediated mentorship recognizes that technology can facilitate rather than replace human relationships (Dysthe et al., 2006). AI serves as an intermediary, helping students prepare for human interactions, practice articulating ideas, and maintain momentum between formal meetings. These mediated interactions can create scaffolding that makes face-to-face exchanges more productive and less anxiety inducing. By enhancing both the quality of mentorship and opportunities for peer collaboration, AI tools can support the social networks that sustain students through the challenges of doctoral work (Vekkaila et al., 2018).

Challenges and Ethical Complexities

As with any new technology, challenges connected to psychological, pedagogical, and ethical dimensions will arise and must be addressed. The literature is consistent with multiple concerns regarding AI use in higher education. For example, Oliveira et al. (2024) noted that some doctoral students fear AI adoption and that this fear must be acknowledged and addressed with a strategy to support them. Without proper support, resistance to AI can intersect with imposterism or low self-efficacy, where AI tools can reinforce those feelings of inadequacy rather than provide support. In addition, student misuse can further extend editing bias (Bender et al., 2021). Applicable training with transparent, ethical guidelines can support doctoral students' understanding of the use of AI to help them reach their goals (Bista & Bista, 2025).

Grichko et al. (2025) and many others noted the need for AI literacy and recommended drafting guidelines and providing training. Literacy initiatives and institutional policy should address both technical solutions, and the pressures students face with time management and ethical use (Archana et al., 2025). When students feel overwhelmed by time constraints, it can lead to improper and even unethical use of AI.

Boyd and Harding (2025) and Rahiman and Kodikal (2024) urged researchers to address privacy and data security issues that may arise when users do not understand the potential risks to their safety and protection. In addition, Boyd and Harding (2025), Van der et al. (2023), and many others point out that there is often a lack of transparency and accountability and recommend that guidelines should be provided for reporting AI use. This can result in a tension whereby encouraging AI use and requiring transparency may discourage experimentation. Yet non-disclosure is also problematic when AI use is invisible to faculty. Through training, feedback, and human mentorship, AI can be reframed to help institutions better understand student gaps and misunderstandings.

The most frequently noted challenges in the literature concern ethical use of AI for writing and researching with students not understanding they cannot just copy and paste results from their query. Migliore (2024) urged users to understand the responsible use of AI, while Zou and Huang (2023) addressed student overuse and the challenge of information accuracy, since AI tools can make mistakes and “hallucinate” source references when sources cannot be easily located. The danger of AI use without training is that students may develop AI literacy but lose the ability to develop independent research skills that will support them professionally. In addition, it could hinder them from becoming experts in their research topic if AI did all the

literature review for them.

The biggest concern for AI use in doctoral programs is plagiarism and ethical misuse (Grichko et al., 2025; Van der et al., 2023; Ziyank & Abrams, 2026). Much of the AI literature acknowledges that many users do not understand the importance of original work and often copy and paste directly from AI tools without verifying their validity. Traditional plagiarism frameworks assume human authorship and intentional deception. However, the advent of AI may begin to challenge the notions of who owns the ideas and how writing assistance infringes on human ideas. The ethics of AI use should be clearly identified for both students and faculty, with clear examples and institutional guidance for both students and faculty (Boyd & Harding, 2025). Beyond individual ethics, systemic issues also surface as AI discussions become more prominent. Most recently, Akbar (2025) pointed out that major tech companies may be violating doctoral students' intellectual property rights by major technology companies conducting large-scale data sweeps. The dissertation represents the hard work and time of students' original research. Companies using it for training data without consent or compensation is a concern for both doctoral programs and students.

Implications for Doctoral Education and Future Directions

While AI offers many resources for doctoral students, and we do advocate for both student and faculty use of AI, we must acknowledge that this has presented challenges for the supervisor (dissertation chair), such as having to search for false references, plagiarism, and even overuse of AI tools for writing. In addition, for supervising faculty, there must be a redesign of pedagogy to best integrate AI student use in the research process (Swindell et al., 2024). Moreover, the importance of teaching students the process and practice of research is even greater as faculty demonstrate AI as a tool and when it should be used as a support for the researcher (Grichko et al., 2025).

Many researchers have urged that clear policy and guidelines that address both ethics and best practice must be established and clearly communicated for doctoral students using AI in the dissertation research (Bista & Bista, 2025; Boyd & Harding, 2025; Grichko et al., 2025; Krumsvik, 2024; Lesh & Lancaster, 2025; Oliveira et al., 2024; Rahiman & Kodikal, 2024). These guidelines should “serve as a foundation for human academic processes and as critical components in the development and refinement of intelligent tools designed to assist and enhance the doctoral journey” (Krumsvik, 2025, p. 9456). Lesh and Lancaster (2024) created an Ethical Use of Generative AI in Doctoral Programs: Compliance Rubric that is an excellent model for doctoral student integration and faculty use of AI tools. The rubric focuses on major areas such as ethical use, plagiarism, attribution, biases, monitoring and evaluation, and training and support and can provide clear expectations for AI use. They also recommend it be used for periodic evaluation and assessment for improvement.

In addition to providing guidelines for student use of AI, doctoral supervisors can demonstrate effective use of AI by providing support resources such as guided tutorials and example prompts for students to use to get started with topic selection or searching for supporting research (Li & Lin, 2025). In fact, Grichko et al. (2025) recommended a gradual introduction throughout the doctoral program. But to do this successfully, faculty should first be

trained and armed with best practices to model effective and ethical use (Bista & Bista, 2025; Oliveira et al., 2024). As with any new technology, institutions must provide ongoing training for continued use of AI as it is quickly evolving. Offering this kind of faculty support will also help with how quickly and effectively a faculty member can integrate the tools.

AI Balance for Doctoral Education

No matter what people think about AI, it has changed society in significant ways. Higher education is shifting from viewing AI as a novel form of learning to recognizing it as a tool for supporting learning. We should move beyond the debate over AI's usefulness and concentrate instead on how it can be applied in specific contexts to benefit students (Johnson et al., 2024). In doctoral programs, AI can support reimagining and alignment with teaching and learning goals, thereby fully supporting doctoral students (Swindell et al., 2024). When doctoral programs create systems that support the AI-augmented scholar, the program supports students' educational and professional journeys by enabling them to learn how to ethically incorporate AI skills effectively (Migliore, 2024). Integrating these skills into the program will increase persistence in doctoral programs by addressing students' varied learning styles while maintaining accountability and clear expectations for research production (Spaulding & Rockinson-Szapkiw, 2012).

Supporting the AI-augmented scholar addresses the educational and affective domains that hinder research output. Tinto's student integration theory (1975) holds that the program environment can foster or hinder resilience and persistence when students are not socially and academically integrated into the institution's norms. As such, addressing the human relationship aspect for scholars is vital to their persistence in the program and beyond. In fact, Lesh and Lancaster (2024) and Henricksen et al. (2024) assert that, to best support the AI scholar, we must balance AI integration, human judgment, and ethical decision making.

AI can provide additional support for doctoral students with technical and basic concerns. However, the human connection between students and faculty is still important to any successful doctoral student journey. Using AI to enhance technical skills creates opportunities for faculty to engage more intentionally when providing in-person support. Research shows that belongingness and academic integration are associated with lower attrition rates (Spaulding & Rockinson-Szapkiw, 2012). Therefore, maximizing the time between students and professors to deepen thinking rather than correcting will support a healthy learning environment and encourage persistence among doctoral students. As a result, if faculty intentionally embed AI-enabled continuous support into the doctoral experience, it can re-imagine the doctoral experience for students by creating additional pathways for support. This kind of student support aligns with research on doctoral persistence, showing that consistent engagement and timely feedback are key predictors of student completion (Gardner, 2009; Jairam & Kahl, 2012).

Finally, for AI to be fully accepted, the field must coalesce around a tacit agreement on what constitutes ethical use and the related transparency of use. Bista and Bista (2025) recommend that to fully harness the current and future capabilities of AI, both faculty and students need training in its proper use and the potential challenges it presents. Maintaining a balance in human interaction is essential to better prepare students to use AI throughout their educational and professional journeys (Bista & Bista, 2025).

Declarations

The authors declare no conflicts of interest

Artificial Intelligence Use Disclosure

AI was used to generate the Figure 1 Conceptive Model image, locate relevant research articles, and some editing of the manuscript.

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Curriculum Mapping as a Tool for Continuous Improvement of the Business Studies (BS) Curriculum in a Digital-First University

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Abstract

In an era defined by rapid technological disruption, labour market volatility, and increasing demands for accountability in higher education, curriculum mapping emerges as a critical strategic tool for ensuring programme coherence, relevance, and quality. This paper presents a comprehensive, theoretically grounded curriculum mapping framework tailored for a digital-first institution, utilising Arden University's School of Business and Creativity as a central case study. The study synthesises existing literature to propose a robust framework for continuous improvement, demonstrates its utility through a detailed application to a contemporary business programme, and proposes evidence-based enhancements addressing the impact of Artificial Intelligence (AI). Adapting the model of Veltri et al. (2011), the proposed multi-dimensional framework systematically maps Programme Learning Outcomes (PLOs), Teaching and Learning Activities (TLAs), and Assessment Methods (AMs) against a matrix of internal attributes and external benchmarks, including QAA Subject Benchmark Statements and World Economic Forum (WEF) skills forecasts. Utilising a qualitative case study approach, the analysis reveals that while Arden University's BA (Hons) Business Management programme possesses strengths in authentic assessment, it requires stronger intentional development of future-ready skills such as AI literacy. Recommendations focus on refining PLOs, creating integrated skill threads, and pioneering AI-aware assessment strategies. This systematic approach allows institutions to move beyond static design to a dynamic model of continuous enhancement.

Keywords: Curriculum mapping, continuous quality improvement (CQI), higher education, curriculum design, digital-first education, artificial intelligence (AI).

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The Imperative for Strategic Curriculum Mapping

Background: The Challenge to Static Curricula in a Disruptive Environment

Higher education institutions in the twenty-first century operate within a landscape characterised by unprecedented velocity and unpredictability. The converging forces of accelerated globalisation, persistent labour market uncertainty, economic instability, and the relentless pace of technological advancement, most notably the rise of artificial intelligence, create a powerful and unavoidable imperative for accountability, efficiency, and transparency in academic programming. Within this volatile context, the traditional academic conception of a curriculum as a fixed, stable, and enduring entity has become fundamentally untenable. It is no longer sufficient to design a programme once and allow it to run unchanged for years; such static entities run the significant risk of rapidly losing relevance in the face of external disruption, rendering graduates ill-equipped for the modern workforce.

To address this existential challenge, universities are increasingly called upon to demonstrate that their academic programmes provide a coherent, aligned, and evolving educational experience. This experience must intentionally develop the knowledge and skills required for professional success and lifelong learning, rather than merely presenting a “bundling of credits.” A robust curriculum must represent an appropriate and progressive sequencing of courses that intentionally scaffolds student learning over time, ensuring that foundational concepts are not just introduced but mastered through reiteration and increasing complexity.

This imperative for coherence is not merely pedagogical but is formalised by the rigorous standards of leading global accreditation agencies. The Association to Advance Collegiate Schools of Business (AACSB), of which Arden University is a member, emphasises that the entire process of learning assurance is rendered meaningless unless a programme’s learning goals are explicitly and systematically addressed within the curriculum it delivers. While the UK’s Quality Assurance Agency for Higher Education (QAA) does not utilise a single statement mirroring the AACSB’s specific phrasing, its regulatory position is embodied in the function and purpose of its QAA Subject Benchmark Statements. The QAA defines national standards and expectations for specific disciplines, which universities are expected to align with to ensure consistency and quality. Consequently, a programme’s curriculum and its learning outcomes must be designed and reviewed in strict alignment with these national standards, ensuring that learning goals are addressed systematically rather than haphazardly. This position aligns closely with the United States’ Accreditation Board for Engineering and Technology (ABET), which mandates that a programme’s curriculum must be rigorously designed to achieve each of its stated learning outcomes.

In response to these converging demands for internal coherence and external accountability, curriculum mapping has emerged as a powerful analytical methodology. As a process, it allows faculty and academic leaders to deconstruct a programme, specify its key components, arrange them in relation to one another in a visual format, and capture an overarching structure that is transparent to all stakeholders. As defined by Harden (2001), curriculum mapping provides clear, accessible information about what is taught, how it is taught, and how student performance is evaluated. This transparency is transformative; it reveals the intricate connections between different curriculum components, helps to identify critical gaps and unnecessary redundancies, and ensures that teaching methods and assessment tools are robustly aligned with broader educational objectives. When institutionalised as a recurring process rather than a one-off administrative task, curriculum

mapping becomes a cornerstone for continuous quality improvement, enabling institutions to navigate the complexities of the modern educational landscape with agility and precision.

The Strategic Context of Arden University

The necessity for a systematic and strategic approach to curriculum mapping is particularly acute for an institution with the specific profile of Arden University. Arden has explicitly defined its market position and institutional identity as being “digital-first,” “innovative,” and committed to a “continually evolving curriculum” that prioritises emerging professions and market disruptions. The mission of its School of Business and Creativity is to combine “traditional business disciplines with creative and innovation-driven thinking to reflect the future of enterprise, leadership, and digital-first organisations.” This ambitious mission demands a curriculum that is not only contemporary in its content but also exceptionally coherent and integrated in its structure and delivery.

For Arden, a predominantly online university with a globally dispersed student body, a well-mapped curriculum is a fundamental necessity rather than a luxury. It provides the core mechanism to ensure a consistent, equitable, and high-quality student experience across diverse delivery modes and international partnerships. Without the transparency provided by a detailed curriculum map, maintaining quality control across decentralised teaching teams becomes exponentially more difficult. Furthermore, documented coherence is essential for maintaining and leveraging memberships with prestigious bodies like the AACSB, the QAA, and multiple professional accreditations from organisations such as the Chartered Management Institute (CMI), Chartered Institute of Marketing (CIM), and the Institute of Leadership and Management (ILM). The framework proposed in this paper is therefore designed to support Arden’s unique institutional values of being “progressive” and “resourceful” by providing a clear methodology to harness technology and accelerate student development, ensuring it delivers the “real-world relevant” education that is central to its vision.

Literature Review

A comprehensive review of the relevant literature establishes the theoretical, practical, and strategic foundations of curriculum mapping as an essential tool for continuous improvement in higher education. This review explores the historical evolution of the practice, its deep roots in learning theory, and the human factors that influence its success.

Foundational Principles and Purpose of Curriculum Mapping

The concept of curriculum mapping as a formal process for educational improvement is not a novel invention, though its application has evolved significantly over recent decades. While Archambault and Masunaga (2015) trace its historical roots to K-12 education in the United States during the 1970s, where it was developed as a pragmatic method for teachers to inventory and align classroom content, there is sufficient evidence to show that the principles related to curriculum mapping were in use in the UK long before the term was popularised by figures like R.M. Harden in the early 2000s.

The historical roots of mapping in the UK can be traced to two distinct strands: a philosophical tradition of curriculum development and a pragmatic response to national education reform. First, the philosophical roots are evident in the “Process Model” championed by Lawrence Stenhouse in the 1970s. Stenhouse argued vehemently against a rigid, top-down, objectives-led curriculum. Instead, he viewed the curriculum as a hypothesis to be tested and refined by teachers in their own classrooms, central to his concept of the “teacher as researcher.” This model encouraged teachers to systematically analyse their own

teaching practices, document the “enacted curriculum” (what was happening in the classroom), and reflect on the alignment between their intentions, their actions, and student learning. This act of critically examining, documenting, and reflecting on the curriculum in action is a direct philosophical precursor to the modern practice of curriculum mapping.

Secondly, the pragmatic driver for curriculum alignment in the UK arrived with the Education Reform Act of 1988, which introduced the National Curriculum for schools in England and Wales. This legislation represented a monumental shift that, for the first time, prescribed specific content (“Programmes of Study”) and “Attainment Targets” for most subjects. This created a systemic, top-down requirement for every school to ensure their teaching covered the mandated content and demonstrated how their schemes of work aligned with the national framework. While not explicitly termed “curriculum mapping” at the time, this process of auditing teaching plans against a set of external standards to ensure coherence and coverage is functionally identical to the core mechanics of modern curriculum mapping.

In the context of higher education, the practice has been adopted as a strategic response to increasing demands from accreditation bodies, employers, and other stakeholders for demonstrable alignment between programme goals and student learning experiences. At its core, curriculum mapping is a method of collecting and analysing data about what is actually being taught to create a visual representation of the curriculum. This process makes the structure of a programme visible, allowing faculty to understand how individual courses fit together and build upon each other.

A crucial principle underpinning this process is the recognition that a single institution may simultaneously operate multiple, often misaligned, versions of its curriculum. Kopera-Frye, Mahaffy, and Svare (2008) identify four distinct curricula: the *written curriculum* (what is stated in official documents), the *taught curriculum* (what is implemented by instructors), the *learned curriculum* (what students gain), and the *assessed curriculum* (what is measured). A primary purpose of curriculum mapping is to force these four versions into alignment, ensuring that what is taught and assessed is a true reflection of the institution’s stated goals. As Harden (2001) argues, an effective curriculum is synergistic, where “the whole is greater than the sum of the individual parts.” The purpose is consistently identified in the literature as threefold: to comprehensively assess the existing curriculum, to facilitate its continuing review, and to support its ongoing enhancement through an evidence-based cycle of reflection and action (Veltri et al., 2011).

Theoretical Underpinnings: The Rationale for Mapping

While curriculum mapping is often viewed as an administrative process, its effectiveness is deeply rooted in established cognitive science and learning theories. The process aligns strongly with Ausubel’s (1962) theory of *meaningful learning*, which posits that learning is most effective when new knowledge is integrated into an existing cognitive structure. As explored by Anastasiou et al. (2024), organising knowledge hierarchically and making relationships between concepts explicit enhances meaningful learning. A curriculum map serves as precisely this kind of “advance organiser” (Willerman & Mac Harg, 1991), visually representing the academic journey and helping students see the relevance of individual topics to their overall development.

The visual clarity of a map also connects directly to *cognitive load theory (CLT)* (Sweller, 1994). CLT suggests that working memory is limited and that instructional design should aim to reduce extraneous cognitive load, the mental effort required to process information that is not essential to the learning task itself. A disjointed, incoherent curriculum imposes a high extraneous cognitive load on students, who must expend precious mental

energy trying to forge connections between isolated courses that are not made explicit. A well-mapped curriculum, with its clear pathways and logical sequencing, provides a higher degree of organisation that assists students in building mental schemas, thereby reducing cognitive load and freeing up working memory for deeper learning.

This leads to the principle of *constructive alignment* (Biggs, 2003), a cornerstone of modern curriculum design. As detailed by Livingstone (2014), constructive alignment demands unity between the Intended Learning Outcomes (ILOs), the Learning and Teaching Activities (LTAs), and the Assessment Tasks (ATs). The “constructive” aspect is based on the theory that students construct meaning from what they do to learn; the “alignment” aspect refers to the instructor’s role in creating a learning environment where those activities are explicitly aligned with achieving the ILOs. Curriculum mapping is the primary tool used to visualise and verify this alignment. It ensures that the verbs used in the ILOs (e.g., “analyse,” “create”) are activated in the LTAs and are the explicit focus of the ATs, pushing students towards a deep approach to learning.

Finally, the process of curriculum mapping is underpinned by *constructivist learning theory*, particularly the social constructivism of Vygotsky (1978). This theory posits that learners build new knowledge through social interaction and collaboration. As Bull (2025) notes, engaging learners in the active organisation of concepts aligns directly with constructivist principles. When implemented through collaborative faculty workshops, the curriculum mapping process becomes a powerful form of professional learning where educators collectively construct a shared understanding of the curriculum and co-create solutions.

The Process as a Catalyst for Continuous Improvement

The literature consistently frames curriculum mapping not as a static audit but as a dynamic, cyclical process for continuous improvement. The map should be a “living document that is updated and assessed regularly” (Joyner, 2016a; Okojie et al., 2022). This iterative cycle involves identifying gaps and redundancies (Joyner, 2016a; Okojie et al., 2022), formulating evidence-based recommendations, implementing changes, and then re-evaluating the impact, a process known as “closing the loop” (Ebel et al., 2020; Joyner, 2016a). A key part of this analysis is ensuring both vertical (‘ $\updownarrow$ ’) coherence (the progressive scaffolding of learning using a taxonomy like “Introduced, Reinforced, Mastered”) and horizontal (‘ $\leftrightarrow$ ’) coherence (the integration of learning across courses at the same level). Figure 3 operationalises both concepts within the case study matrix, where the I–R–M progression is read vertically (top to bottom across levels), while the horizontal coherence indicators identify where horizontal integration is strong or at risk. This scaffolding is often discussed in terms of a spiral curriculum, where students revisit topics at increasing levels of difficulty, allowing them to deepen their learning and apply it in new contexts (Lam & Tsui, 2013).

Evaluation Against the Arden University Model

The reviewed literature provides a robust foundation for evaluating the role of curriculum mapping within the specific context of Arden University. For a digital-first, geographically dispersed institution, the transparency and consistency afforded by a comprehensive map are not merely beneficial but essential for quality assurance and the delivery of an equitable student experience. The map provides a central, shared understanding that ensures all tutors are working towards the same learning goals. Arden’s commitment to a “continually evolving curriculum” is directly enabled by the continuous improvement cycle at the heart of the mapping process (Veltri et al., 2011). Furthermore, the imperative for

Arden to prepare students for a future shaped by AI makes mapping a critical strategic tool for planning and verifying the systematic integration of these new skills across the curriculum (Alam & Benaida, 2022). Finally, innovative approaches like the “virtual courses” concept described by Bateman et al. (2015) offer a pragmatic strategy, aligned with Arden’s innovative identity, for tracking cross-cutting digital and professional skills across the programme without requiring major structural redesign.

Methodology

This study employs a qualitative, descriptive case study methodology to develop, apply, and refine a comprehensive framework for curriculum mapping within a specific institutional context. The overarching research paradigm is interpretive, seeking to generate a deep, contextualised understanding of a complex, real-world phenomenon rather than producing generalisable statistical findings (Yin, 2018). A case study approach is particularly appropriate for this research as it excels at providing an in-depth, holistic analysis of a specific, bounded system, in this instance, the curriculum of the BA (Hons) Business Management programme at Arden University. This method is ideal for answering the “how” and “why” questions that are central to this paper: namely, how can a curriculum mapping framework be designed for a digital-first university, and why is such a framework a critical tool for continuous improvement in the current higher education landscape? (Arafeh, 2016). The research design is not intended to test a hypothesis in the positivist sense, but rather to construct a rich, evidence-based argument through a multi-stage process of theoretical synthesis and detailed documentary analysis.

Research Design: A Multi-Stage Approach

The research was conducted using a four-stage qualitative design that integrates theoretical framework development with practical application through systematic documentary analysis, as illustrated in Figure 1. This approach ensures that the resulting framework is both grounded in established scholarship and directly relevant to the practical challenges of the case under investigation.

Figure 1

Figure 1 Multi-Stage Qualitative Research Design. Source: Author's own conceptualisation.

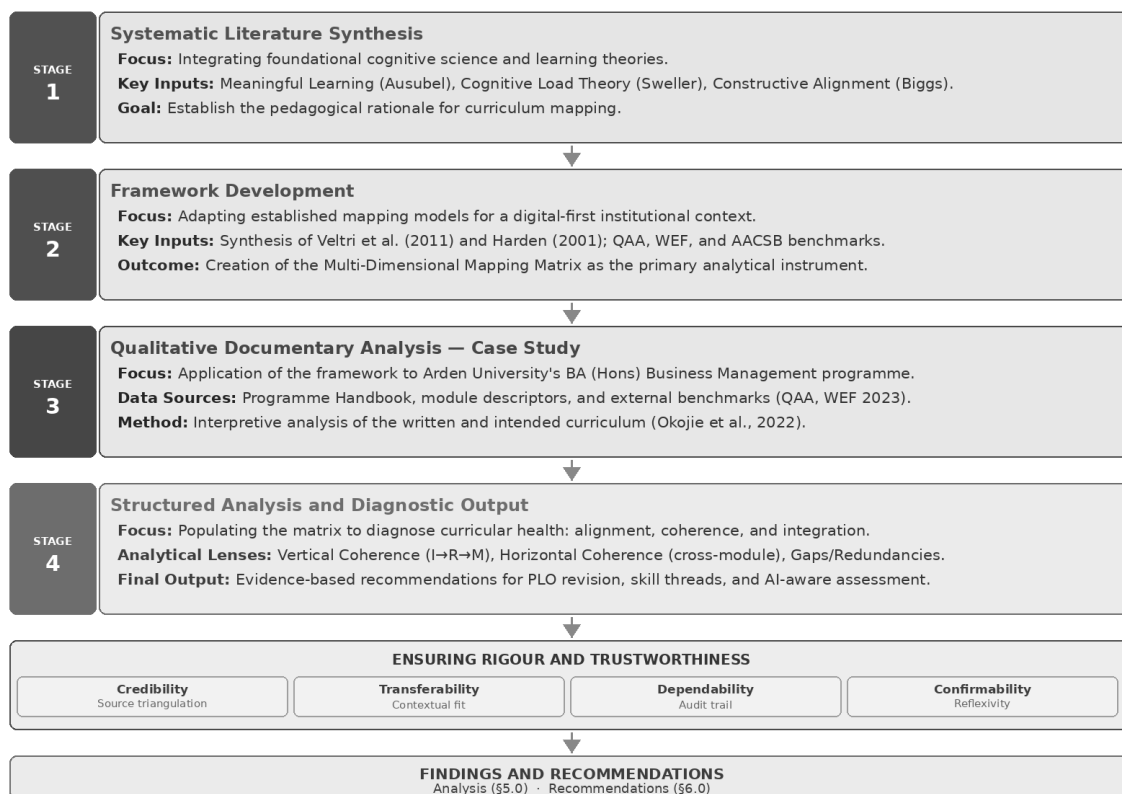


Figure 1. Multi-Stage Qualitative Research Design.
 Source: Author's own conceptualisation.

Stage 1: Systematic Literature Synthesis. The initial stage involved a systematic and thematic review of the literature to synthesise a best-practice theoretical framework. This process drew heavily on foundational models for continuous improvement cycles presented by Veltri et al. (2011) and the faculty-centric perspectives offered by researchers such as Joyner (2016a, 2016b) and Rawle et al. (2017). The theoretical underpinnings of the framework were strengthened by integrating insights from the literature on cognitive science and constructivism, particularly regarding meaningful learning, cognitive load, and constructive alignment (Anastasiou et al., 2024; Bull, 2025; Livingstone, 2014). This rigorous synthesis resulted in the creation of the comprehensive framework detailed in Section 4.0, which serves as the primary methodological and analytical instrument for this study.

Stage 2: Framework Development. Building on the Stage 1 synthesis, the second stage focused on framework development, by adapting established mapping models specifically for a digital-first institutional context. This involved synthesising the models of Veltri et al. (2011) and Harden (2001) with the QAA Subject Benchmark Statement (2023), WEF Future of Jobs forecasts (2023), and AACSB guidance on AI literacy. The primary outcome of this stage was the creation of the multi-dimensional mapping matrix, the analytical instrument described in detail in Section 4.2 and illustrated in Figure 3, which served as the central tool for all subsequent analysis.

Stage 3: Qualitative Documentary Analysis—Study. The third stage applied the framework developed in Stage 2 to the specific case of Arden University's BA (Hons) Business Management programme. Employing a qualitative documentary analysis approach,

this stage treated programme documents not as objective truths but as social artefacts created within an organisation to serve specific purposes (Atkinson & Coffey, as cited in Okojie et al., 2022). The data consisted of publicly available documents, the programme handbook, module descriptors, and external benchmarks (QAA, 2023; WEF, 2023), which were systematically analysed using the multi-dimensional mapping matrix as the primary interpretive lens, as depicted in Figure 3.

Stage 4: Structured Analysis and Diagnostic Output. The final stage involved the structured analysis of the populated matrix to produce a diagnostic output regarding the programme’s curricular health. This stage examined the data through three analytical lenses: alignment with external benchmarks (QAA and WEF), vertical coherence (the progressive scaffolding of skills using the *introduced–reinforced–mastered* framework across Levels 4, 5, and 6), and horizontal coherence (the integration of transferable skills across modules at the same level). The findings of this diagnostic analysis, presented in Section 5.0, form the evidence base from which the strategic recommendations in Section 6.0 are logically and transparently derived.

Data Sources and Selection Criteria

A purposive selection of documents was used to inform both the framework development and the case study analysis. The credibility of a documentary analysis rests on the authenticity and relevance of the chosen sources (Okojie et al., 2022). The sources for this study fall into three main categories, each selected to serve a specific function in the research design.

The first category consists of the *primary academic literature* provided for the study. The core of the research is built upon a detailed review of peer-reviewed articles that form the scholarly conversation around curriculum mapping. Key sources included Veltri et al. (2011) for its comprehensive IS model; Joyner (2016b) for its empirical insights into faculty perceptions and resistance; Anastasiou et al. (2024) for its theoretical discussion of learning principles; Rawle et al. (2017) for its analysis of cross-disciplinary differences; and Saad (2014) and Kopera-Frye et al. (2008) for their practical perspectives on implementation. These sources were selected for their direct and scholarly relevance to curriculum mapping theory and practice.

The second category comprises *grey literature and external benchmarks*. To ensure the framework’s relevance and alignment with current professional and quality standards, key “grey literature” sources were analysed. These included the QAA Subject Benchmark Statement for Business and Management (2023), the World Economic Forum’s Future of jobs report 2023 [Report], and guidance on AI in business education from the AACSB. These documents, while not peer-reviewed in the traditional sense, represent authoritative external standards and industry forecasts against which a modern UK business curriculum must be benchmarked.

The third category is the *case study documents*. The specific application of the framework relied on the analysis of documents pertaining to Arden University. These included the BA (Hons) Business Management Programme Handbook, publicly available module descriptions, and strategic statements published on the university’s website. These documents were selected as they provide the necessary data on the “written curriculum,” including Programme Learning Outcomes (PLOs), course structures, and assessment strategies for the case study analysis.

Data Analysis: The Mapping Process as an Analytical Tool

The analysis of the collected documents was conducted in a structured manner, using the proposed curriculum mapping framework as the primary analytical tool. The literature itself was subjected to a *thematic synthesis*, where arguments and findings from different sources were grouped into the key themes presented in the literature review (Section 2.0), such as foundational principles, theoretical underpinnings, and implementation challenges. This approach allowed for a deeper and more integrated understanding of the scholarly conversation.

For the case study application, the primary analytical instrument was the master curriculum map matrix. This matrix functions as a tool for conducting a structured qualitative content analysis of the curriculum documents (Arafeh, 2016). The analysis involved a conceptual “populating” of the matrix based on the information contained within the programme handbook and module guides. This diagnostic process was guided by a set of specific analytical questions derived from the literature on curricular coherence (Hatzakis et al., 2007) and programme assessment (Ebel et al., 2020):

- a) **Alignment:** Are the Programme Learning Outcomes aligned with external benchmarks (QAA, WEF) and internal institutional attributes?
- b) **Vertical Coherence:** Is there evidence of progressive scaffolding, with skills being clearly Introduced, Reinforced, and Mastered across the levels of the programme?
- c) **Horizontal Coherence:** Are key transferable skills integrated across different modules at the same level, or do they exist in isolated “silos”?
- d) **Gaps and Redundancies:** Are there significant gaps where key outcomes or skills are not adequately addressed? Conversely, are there redundancies where content is repeated without adding value or complexity?
- e) **Strategic Integration:** Is the integration of critical cross-curricular themes, particularly Artificial Intelligence, intentional, systematic, and progressive?

The findings of this structured analysis, presented in Section 5.0, form the evidence base from which the final recommendations are logically and transparently derived.

Ensuring Rigour and Trustworthiness

In line with qualitative research principles, the rigour of this study is addressed through the concept of trustworthiness, which encompasses credibility, transferability, dependability, and confirmability.

Credibility is established primarily through the *triangulation of sources*. The proposed framework is not based on a single author’s opinion but is a synthesis of multiple peer-reviewed academic papers, professional body guidelines, and institutional documents. This triangulation ensures that the framework is robust and well-grounded in a broad range of evidence.

Transferability refers to the extent to which the findings can be applied to other contexts. While the specific findings are context-bound to the Arden University case, the detailed description of the methodological process and the synthesised framework itself are designed to be transferable. Other institutions can adapt this framework and analytical

process to their own programmes, achieving what Yin (2018) refers to as “analytical generalisation” rather than statistical generalisation.

Dependability and **Confirmability** are addressed through the transparency of the research process. This paper explicitly lays out the research design, the data sources, the structure of the analytical framework, and the steps taken to analyse the case study documents. This creates a clear “audit trail,” allowing the reader to follow the logic from the initial data sources through to the final conclusions and recommendations, ensuring the findings are grounded in the evidence presented. Finally, a degree of reflexivity is maintained by acknowledging that the analysis represents an interpretation of the documents, and the structured, evidence-based nature of the methodology is employed to mitigate personal bias and ensure the argument is built upon a solid scholarly foundation.

A Proposed Framework for Curriculum Mapping and Continuous Improvement

This section details the comprehensive curriculum mapping framework proposed for Arden University’s School of Business and Creativity. The framework is not presented as a rigid prescription, but as a dynamic and adaptable methodology for continuous quality improvement. It represents a deliberate synthesis of best practices identified in the literature, adapting the foundational models of Veltri et al. (2011) and Harden (2001) for the specific context of a contemporary, digital-first higher education institution. The framework is designed to be a vehicle for collaboration, a tool for strategic planning, and a mechanism for ensuring that the curriculum remains aligned, coherent, and resilient in the face of ongoing technological and societal change. It is structured around two core elements: a multi-layered architectural model of the curriculum’s components and a systematic, five-step cyclical process for its implementation and review.

Framework Architecture: Components of a Coherent Curriculum

To effectively analyse a curriculum, it must first be deconstructed into its core components. This framework is built upon four interconnected architectural elements: programme learning outcomes (PLOs), course-level learning outcomes (CLOs), teaching and learning activities (TLAs), and assessment methods (AMs). The systematic exploration of the relationships between these four components is the key to ensuring alignment, from the highest-level programme goals down to the specific activities and assessments in each module. Figure 2 provides a visual overview of how these components are architecturally connected within the proposed framework.

Figure 2

Components of a Coherent Curriculum — The Framework Architecture. (Source: Author's own conceptualisation.)

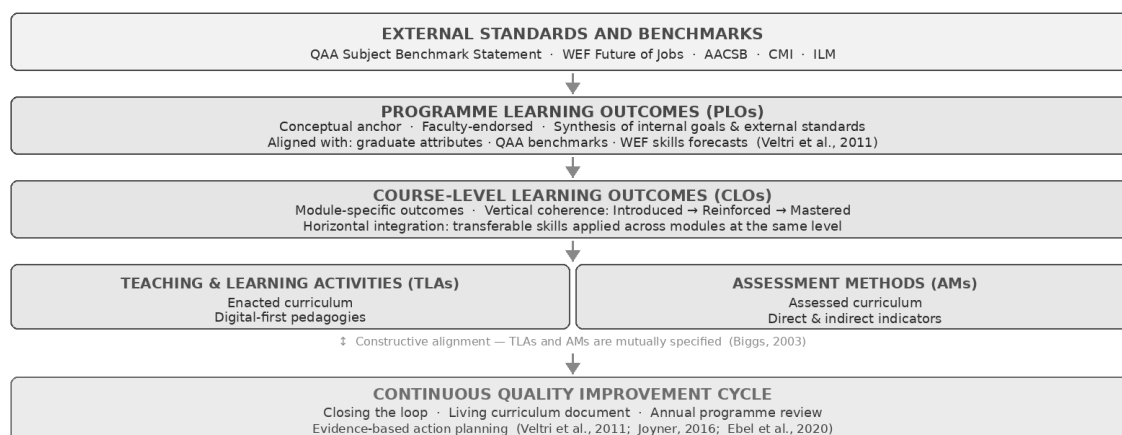


Figure 2. Components of a Coherent Curriculum — The Framework Architecture.
Source: Author's own conceptualisation.

Programme learning outcomes (PLOs) serve as the conceptual anchor for the entire mapping process. These are the high-level statements describing the integrated knowledge, skills, and attributes a graduate is expected to possess upon completion of the programme. For these outcomes to be effective, the literature suggests they must be a synthesis of internal institutional goals and external quality and industry benchmarks (Ebel et al., 2020; Oliver et al., 2007). In the context of Arden University, this means the PLOs should represent a clear alignment between the university's own graduate attributes, the national standards defined in the QAA Subject Benchmark Statement for Business and Management (2023), and the future-of-work skills identified by global bodies like the World Economic Forum (2023). Well-developed, faculty-endorsed statements of intended programme learning outcomes provide the coherent and defensible starting point from which all subsequent analysis proceeds (Veltri et al., 2011).

Course-level learning outcomes (CLOs) are the more granular, specific, and demonstrable outcomes defined for each individual module. While PLOs describe the graduate, CLOs describe what a student will be able to do at the end of a specific course. The mapping process critically examines the vertical and horizontal alignment of these CLOs, ensuring that each one contributes intentionally and progressively to one or more of the overarching PLOs. This creates a clear line of sight, allowing faculty and students to understand the purpose of each course within the broader programme structure.

Teaching and learning activities (TLAs) represent the “taught” or “enacted” curriculum, the pedagogical methods and tools used to deliver course content and facilitate the development of student skills (Kopera-Frye et al., 2008). In a well-aligned curriculum, TLAs are not arbitrary; they are intentionally designed to engage students in the specific activities that will enable them to achieve the stated learning outcomes. This principle is the heart of *constructive alignment*, which argues that learning is constructed by what the student does, and therefore the TLAs must activate the same verbs as the learning outcomes (Livingstone, 2014; Biggs, 2003). For Arden's digital-first context, this component would include a rich mix of online collaborative exercises, case study analyses, and the use of advanced tools like business simulation software.

Assessment methods (AMs) constitute the “assessed curriculum” (Kopera-Frye et al., 2008) and are the instruments used to measure and provide evidence of student achievement. In an aligned system, assessment tasks are not separate from the learning process but are an integral part of it, designed to allow students to demonstrate their mastery of the ILOs (Livingstone, 2014). This framework embraces Arden’s commitment to authentic, non-exam-based assessments, but stresses that each assessment must be explicitly mapped back to the outcomes it purports to measure. Furthermore, the framework incorporates the distinction between direct indicators of learning (e.g., student performance in specific assignments) and indirect indicators (e.g., student exit surveys or employer feedback), both of which are essential for a holistic evaluation of the curriculum’s effectiveness (Ebel et al., 2020).

The Analytical Instrument: The Multi-Dimensional Mapping Matrix

The central instrument of this framework is the *master curriculum map matrix*. It functions as a visual representation (Joyner, 2016a), a graphic portrayal (Kopera-Frye et al., 2008), and a data recording tool (Veltri et al., 2011) that makes the entire curriculum transparent. Its structure is intentionally more complex than a simple two-dimensional map, designed to capture the multiple layers of outcomes and standards that a modern business programme must meet. In this matrix, the programme’s courses and other key experiences are listed as rows, while the various outcomes and external benchmarks are listed as columns. A representative example of this matrix, populated with data from the Arden University case study, is presented in Figure 3.

Figure 3

Multi-Dimensional Mapping Matrix — BA (Hons) Business Management Programme. I = Introduced; R = Reinforced; M = Mastered. ↑ = Vertical coherence; ↔ = Horizontal coherence; △ = Gap/integration risk. [Source: Author’s own mapping, adapted from Veltri et al. (2011); aligned with QAA (2023) and WEF (2023)].

Module	Lvl	PLO 1 Business	PLO 2 Critical	PLO 3 Digital	PLO 4 Comm.	PLO 5 Ethics	QAA Bench.	WEF Skills	Coherence Indicator
Level 4 — Introduction (I = skills first encountered)									
BUS4012 Business Finance	4	I	I	—	I	—	I	—	↑ Intro △ No digital
BUS4013 Technology & Innovation	4	—	I	I	I	I	I	I	↑ Intro ↔ Linked L4
Level 5 — Development & Reinforcement (R = skills applied across modules)									
BUS5015 Data Analytics & Mgmt	5	R	R	R	—	—	R	R	↑ R from L4 △ Silo risk
BUS5016 Business Start-up	5	R	R	—	R	—	R	R	↑ R from L4 ↔ Partial
BUS5023 Digital & Social Media	5	R	R	R	R	—	R	R	↑ R from L4 △ Gap: PLO3
Level 6 — Mastery & Integration (M = skills demonstrated at programme level)									
BUS6009 Intl Business Mgmt	6	M	M	R	M	—	M	M	↑ M: PLO1-2 ↔ Strong
BUS6010 Strategic Management	6	M	M	R	M	M	M	M	↑ Full M ↔ Strong
BUS6012 Governance, Law & Ethic	6	—	M	R	M	M	M	R	↑ M: PLO2 △ PLO5 gap
I = Introduced R = Reinforced M = Mastered — = Not mapped ↑ Vertical coherence ↔ Horizontal coherence △ Gap/integration risk									

Figure 3. Multi-Dimensional Mapping Matrix — BA (Hons) Business Management Programme.
Source: Author’s own mapping, adapted from Veltri et al. (2011); aligned with QAA (2023) and WEF (2023).

The power of this matrix lies in its multi-dimensional nature. It allows curriculum committees to move beyond asking “Is this topic covered?” to asking far more sophisticated, strategic questions. For example, it enables an analysis of how a single module, such as ‘Project Management’, contributes not only to its own CLOs but also simultaneously to a university-wide Graduate Attribute (e.g., ‘Effective Communication’), a professional body competency (e.g., CMI’s ‘Project Leadership’), and a future-focused skill identified by the WEF (e.g., ‘Leadership and social influence’). This provides a powerful analytical view essential for strategic curriculum management, accreditation, and communicating the value of the programme to students (Archambault & Masunaga, 2015).

The Process: A Five-Step Cycle for Continuous Improvement

Implementing the framework involves a systematic, cyclical process designed to foster professional dialogue and lead to tangible curriculum enhancements. This five-step cycle adapts the models proposed by Veltri et al. (2011) and others, emphasising a collaborative and evidence-based approach.

Step 1: Defining outcomes and external benchmarks. The cycle begins with the critical task of establishing a clear, measurable, and robust set of PLOs. As Veltri et al. (2011) caution, unless the outcomes are developed and agreed upon by programme faculty, the entire mapping exercise risks being meaningless. This stage involves not only internal deliberation but also a thorough analysis of external benchmarks, including QAA statements and professional body requirements, to ensure the programme's external validity and relevance.

Step 2: Collaborative mapping and data collection. This stage involves faculty convening in collaborative workshops to populate the master curriculum map matrix. This process is crucial not only for accurate data entry but, more importantly, for promoting the professional dialogue that lies at the heart of curriculum improvement (Joyner, 2016b). While course syllabi serve as the primary data source for the “intended” and “communicated” curriculum (Arafeh, 2016), the faculty dialogue during these workshops is essential for capturing a more accurate picture of the “enacted” curriculum, what actually happens in the classroom.

Step 3: Analysis and diagnosis of the map. Once populated, the map is systematically analysed to diagnose the health of the curriculum. This is the core analytical phase, where the committee looks for specific patterns. This includes identifying gaps, where PLOs or key skills are under-addressed, and redundancies, where concepts are repeated without progression. It is crucial here to distinguish between harmful redundancy and desirable reinforcement within a spiral curriculum (Joyner, 2016a; Lam & Tsui, 2013). The analysis also focuses on identifying misalignments between the stated level of instruction and the associated assessments, as well as skill silos, which indicate a lack of horizontal integration.

Step 4: Evidence-based action planning. This stage involves translating the diagnosis from the map into specific, actionable recommendations for improvement. Crucially, this is not based on the map alone. As recommended by Ebel et al. (2020), the findings from the map should be triangulated with other sources of evidence, such as direct assessment data from student work and indirect assessment data from student satisfaction surveys, alumni feedback, and employer interviews. This ensures that the resulting action plan is holistic and evidence-based.

Step 5: Closing the loop—Integration with quality cycles. The final and most critical step is to ensure the curriculum map does not become a static document. It must be institutionalised as a “living document” that is integrated into formal quality assurance processes, such as annual programme review (Joyner, 2016a). This step “closes the loop” by using the outcomes of implemented changes and new assessment data to validate or challenge the map, which then becomes the starting point for the next iteration of the continuous improvement cycle (Ebel et al., 2020).

Application and Analysis: A Case Study of Arden University's Business Studies Programme

This section presents the analytical core of the study, detailing the application of the comprehensive curriculum mapping framework (outlined in Section 4.0) to the specific case of Arden University's BA (Hons) Business Management programme. The analysis is based on a qualitative documentary analysis of the publicly available programme handbook and associated module descriptors. The framework is employed here as a diagnostic tool to evaluate the programme's alignment with external benchmarks, to assess its internal coherence, and to critically examine its strategic integration of contemporary themes, particularly artificial intelligence (AI). The findings are presented not merely as a report of data, but as an interpretive analysis that connects the structure of the curriculum back to the theoretical principles and practical challenges identified in the literature review.

Analysis of Programme Learning Outcomes (PLOs): Benchmarking Against External Standards

The first stage of the analysis involves a critical evaluation of the programme's stated Programme Learning Outcomes (PLOs), which serve as the "conceptual anchor for the mapping exercises." A robust set of PLOs must reflect a synthesis of internal institutional goals and external quality and industry benchmarks. A comparative analysis of the BA (Hons) Business Management programme's existing PLOs against the UK's Quality Assurance Agency (QAA) *Subject Benchmark Statement for Business and Management* (2023) and the top skills identified in the World Economic Forum's (WEF) *Future of Jobs Report 2023* reveals a solid foundation in core business functions, but also significant opportunities for strategic enhancement.

The current PLOs demonstrate a strong alignment with the traditional knowledge areas expected of a business degree, such as understanding key business functions and the external environment, which are consistent with the QAA benchmarks. However, the analysis reveals that the PLOs are less explicit in articulating the higher-order cognitive skills and future-focused competencies that are now central to both the revised QAA statement and the WEF report. For instance, while PLO 7 mentions "critical thinking," the WEF's more nuanced distinction between "analytical thinking" and "creative thinking" is not explicitly captured. This lack of specificity can lead to ambiguity in curriculum design and assessment.

Most notably, the analysis identifies a significant gap, in that there is no explicit mention in the PLOs of AI, advanced data analytics, or sustainability as core, named competencies for graduates. Given the WEF (2023) identifies "AI and big data" and "Technological literacy" as top-priority skills, their absence from the programme's highest-level outcome statements is a strategic weakness, particularly for an institution with a "digital-first" mission. Leading bodies like the AACSB (2023) are now advocating for an "inclusive AI literacy" that combines technical skills with a deep understanding of ethical considerations. Without an explicit PLO mandating this, the development of such a critical, cross-curricular competency is left to chance rather than being systematically designed. The language of the PLOs could be substantially strengthened to better reflect the expectation that graduates will not just understand but critically evaluate, innovate, and lead in a technology-driven and ethically complex world.

Diagnosing Curricular Coherence: A Conceptual Heat Map Analysis

As illustrated in Figure 3, the application of the multi-dimensional mapping matrix to the programme's structure allows for a conceptual "heat map" analysis to diagnose its internal coherence. This process involves visually mapping where PLOs and key skills are

introduced (I), *reinforced* (R), and *mastered* (M) across the sequence of core modules; the Coherence Indicator column on the right of the matrix makes explicit where vertical scaffolding is strong, where horizontal integration is present, and where gap risks have been identified. This analysis reveals a curriculum with considerable strengths in vertical coherence but significant weaknesses in horizontal integration.

The programme demonstrates strong *vertical coherence* in its foundational subject areas. For example, a student's journey in understanding financial principles can be clearly traced. The concept is likely "Introduced" at Level 4 in a module like *BUS4012 Introduction to Business Finance*, "Reinforced" at Level 5 where it is applied in a module such as *BUS5016 Business Start-up* and finally integrated and applied at a strategic level for "mastery" in a Level 6 capstone module. This progressive scaffolding aligns with the principles of a spiral curriculum, where topics are revisited at increasing levels of difficulty to deepen learning. This structure provides a clear and logical pathway for student development in core disciplinary knowledge.

However, the analysis also points to a significant challenge in *horizontal integration*, a common issue where learning becomes siloed within individual modules. For instance, the crucial skills taught in the Level 5 module *BUS5015 Data Analytics & Management* risk becoming an isolated "hot spot" of competence. The mapping process forces the critical question, which is, "Are students then required to apply these data analysis skills in their other Level 5 and Level 6 modules, such as *BUS5023 Digital & Social Media Marketing* or *BUS6009 International Business Management*?" If the map reveals that these skills are taught and assessed in one module but not explicitly drawn upon or required in others at the same level, it indicates a lack of horizontal integration. This prevents students from developing the ability to transfer and apply their learning in new and varied contexts, a core goal of higher education. In such a scenario, the curriculum functions more as a collection of discrete, valuable topics rather than a truly integrated programme designed to build cumulative, transferable capability, failing to meet Harden's (2001) ideal of a curriculum where the "whole is greater than the sum of the individual parts."

Analysis of Strategic AI Integration: From Isolation to Infusion

A targeted audit of the curriculum's engagement with artificial intelligence, a theme critical to Arden's mission, reveals a structural issue of isolation rather than infusion. The current module list suggests that technology topics are concentrated in specific courses like *BUS4013 Technology & Innovation*. While such modules are valuable, this structure risks positioning AI as a specialised topic rather than integrating it as a foundational, cross-cutting tool and competency, a key recommendation from leading business schools. A future-ready curriculum would see AI principles applied not just in technology modules, but also in marketing (e.g., AI-driven consumer analytics), finance (e.g., algorithmic trading), and HR (e.g., AI in recruitment).

This isolation also impacts the treatment of ethics. While a module like *BUS6012 Governance, Law & Ethics* provides a natural home for discussing the societal implications of technology, separating this discussion from the technical and strategic application of AI is a missed opportunity. The ethical dimensions of AI, such as algorithmic bias and data privacy, are most powerfully understood when they are confronted directly within the contexts where the tools are being used. Finally, the analysis reveals a lack of clear, progressive skill development in AI literacy. Best practice suggests that students should be scaffolded from simple tasks (e.g., using generative AI for brainstorming in a Level 4 module) to more advanced applications (e.g., using AI for data analysis or critically evaluating AI-generated strategies in a Level 6 project). The current structure does not make this developmental

pathway explicit. This points to a fundamental disconnect between having modern module titles and achieving the systematic, progressive development of the underlying digital and AI competencies throughout the entire student journey. The curriculum must be redesigned to treat AI as a fundamental competency and a “partner” for thought, not just a topic of study (Veltri et al., 2011).

Recommendations and Implications

The application of the curriculum mapping framework to Arden University’s BA (Hons) Business Management programme, as detailed in the preceding analysis, provides a clear, evidence-based foundation for a series of actionable recommendations for programme enhancement. The overarching finding is that while the programme possesses a strong vertically coherent structure and a commitment to authentic assessment, significant opportunities exist to enhance its horizontal integration, strategic alignment with external benchmarks, and its pedagogical approach to emerging technologies, particularly Artificial Intelligence. The following recommendations are therefore designed not as minor adjustments, but as a strategic roadmap for evolving the curriculum to fully meet the demands of a digital-first educational mission. The implications of this analysis extend beyond the single case, offering a model for how similar institutions can approach continuous, evidence-based curriculum improvement.

Recommendation: Enhance Programme Design Through PLO Articulation

The analysis revealed that while the current Programme Learning Outcomes (PLOs) provide a solid foundation in core business functions, they lack the specificity and ambition required to drive the development of future-focused competencies. As Veltri et al. (2011) argue, PLOs serve as the “conceptual anchor” for the entire curriculum; if critical skills like AI literacy, advanced data analytics, and sustainability are not explicitly articulated at this highest level, their development within the programme’s modules will likely remain inconsistent and ad-hoc.

Therefore, the first and most fundamental recommendation is to revise the BA (Hons) Business Management PLOs to be more explicit about higher-order cognitive skills and strategic themes. This revision should be directly informed by the key external benchmarks identified in this study. The language should be sharpened to reflect the expectation of critical evaluation, innovation, and leadership, drawing directly from the QAA Subject Benchmark Statement for Business and Management (2023) and the skills forecast of the World Economic Forum (2023). For example, a revised PLO might state; “Critically evaluate and apply emerging technologies, including AI and data analytics, to generate innovative and ethical solutions to complex business problems.” A similarly revised outcome focused on sustainability could be introduced. This stronger articulation provides a clearer and more ambitious target for the entire curriculum, establishing an unambiguous mandate for course designers and ensuring that programme design is driven by explicit, relevant, and measurable goals, a core principle of accreditation bodies like the QAA and AACSB.

Recommendation: Optimise Course Design by Creating Integrated “Skill Threads”

A primary finding of the analysis was the identification of “skill silos,” where critical competencies are taught in isolated modules, leading to weak horizontal integration. To address this, the curriculum should be intentionally restructured to create clear, integrated “threads” for these transferable skills, particularly data analytics and AI literacy. This involves a systematic plan to ensure these skills are explicitly Introduced at Level 4, Reinforced and applied across multiple disciplinary contexts at Level 5, and required for Mastery in Level 6 capstone modules, which is a progression made visible in Figure 3, where

the coherence indicator column identifies PLO 3 (digital literacy) as presenting a horizontal integration gap at Level 5 that this restructuring directly addresses. This approach directly operationalises the concept of a spiral curriculum, where students revisit concepts with increasing complexity to deepen their learning (Lam & Tsui, 2013).

This would transform the curriculum from a collection of discrete topics into an integrated learning journey that fosters more transferable competence (Harden, 2001). For instance, after being introduced to data analytics techniques in *BUS5015*, students should then be explicitly required to apply those techniques in their marketing plans in *BUS5023* and in their strategic analyses in *BUS6010*. This would require a coordinated effort among module leaders to design assignments that build upon prior learning, a collaborative process that the curriculum map itself is designed to facilitate (Joyner, 2016b). Such an approach ensures that the “whole of the curriculum is greater than the sum of the individual parts” (Harden, 2001) and moves students from simply knowing a skill to being able to use it flexibly and confidently.

Recommendation: Innovate Assessment to Be AI-Aware and AI-Centric

The analysis highlighted that for a digital-first university, the most critical pedagogical shift required is in its approach to assessment in the age of AI. Therefore, it is recommended that Arden’s authentic assessment strategy be evolved to be explicitly AI-aware and AI-centric. This requires moving beyond a defensive posture of trying to “AI-proof” assignments and instead designing assessments that actively leverage AI to foster and measure the higher-order thinking skills that are now more important than ever. This is a direct application of the principle of *constructive alignment* (Biggs, 2003; Livingstone, 2014); if the new PLOs require students to “critically evaluate” the use of AI, then the Assessment Tasks (ATs) must be designed to elicit and measure that specific skill.

This can be achieved through several innovative assessment designs. One such design is the *AI-Assisted Strategy Development* task. In this assignment, students would use a generative AI tool to brainstorm multiple strategic options for a business problem. The student’s assessed work would not be the AI output, but a subsequent report that critically evaluates the AI-generated options, identifies their strengths and weaknesses using external evidence, and provides a reasoned justification for selecting and refining the most viable strategy. A second design is the *AI Output Critique*, where students are provided with an AI-generated business report and are tasked with identifying inaccuracies, logical fallacies, biases, and “hallucinations,” and then producing a corrected and improved version. A third critical component would be a *Mandatory Process Reflection*, requiring students to submit a statement disclosing which AI tools they used and critically reflecting on how AI shaped their analysis and conclusions. These assessments shift the focus from the simple production of content to the metacognitive and critical skills essential for ethical and effective technology use in the workplace.

Recommendation: Institutionalise the Mapping Process for Sustainable Improvement

For any of these enhancements to be sustainable, the process of curriculum mapping must be embedded within the university’s quality culture. Therefore, a final key recommendation is that the *Master Curriculum Map Matrix* be formally adopted as a core governance document within the School of Business and Creativity’s annual programme review and quality assurance cycle. This ensures that curriculum mapping is not a one-off project but becomes a sustainable, embedded practice for continuous improvement, as Veltri et al. (2011) intended.

As the literature on implementation challenges makes clear, faculty buy-in is essential and can be difficult to maintain if the process is perceived as a burdensome, top-down mandate (Joyner, 2016b). By institutionalising the map as a central tool for all curriculum discussions, it becomes an indispensable part of the professional dialogue. It ensures that decisions about programme changes are always evidence-based and strategically aligned with internal goals and external benchmarks. This creates a “living document” and formally “closes the loop” of the assessment cycle (Ebel et al., 2020; Joyner, 2016a), providing the mechanism for the curriculum to remain agile and responsive to future changes in technology, industry, and accreditation standards.

Implications for Practice and Future Research

The implications of this study extend beyond the specific recommendations for the Arden University programme. Firstly, for Arden and similar digital-first institutions, this research provides a clear model for how to move from a curriculum that simply includes digital topics to one that is holistically designed for a digital world. It highlights that true digital transformation in education is a matter of curriculum structure and pedagogical strategy, not just technological tools. Secondly, the proposed framework is highly transferable. Other higher education institutions, particularly those undergoing accreditation review or strategic renewal, can adopt this methodology to conduct their own evidence-based analysis. The process of synthesising external benchmarks, mapping internal coherence, and fostering faculty dialogue is a universal model for effective curriculum governance.

Finally, this study points to several avenues for future research. An empirical study could be conducted to measure the impact of implementing these recommendations on student performance, engagement, and perceptions of work-readiness. Longitudinal research could track how the development of “skill threads” affects long-term knowledge retention and transfer. Furthermore, as AI-aware assessments are implemented, research will be needed to evaluate their effectiveness and to develop reliable and valid methods for assessing the new and complex skills they target. Such research will be critical as higher education continues to navigate its relationship with artificial intelligence.

Conclusion and Future Directions

Synthesis of the Argument and Key Findings

This paper addressed the critical challenge facing higher education institutions, particularly digital-first providers like Arden University, where there is a need to ensure that curricula are coherent, relevant, and dynamically aligned in an era of profound technological and societal disruption. It confronted the risk of curricula becoming static, misaligned collections of credits rather than intentionally designed learning journeys. To address this, this study developed, applied, and evaluated a comprehensive curriculum mapping framework as a strategic tool for continuous, evidence-based improvement. The central argument of this paper is that a systematic, collaborative, and theoretically grounded approach to curriculum mapping is not merely a quality assurance exercise, but an essential practice for any institution committed to delivering on its promise of a high-quality, future-ready education.

The application of this framework to the case study of Arden University’s BA (Hons) Business Management programme yielded several critical findings that underscore the utility of the process. Firstly, the analysis of the Programme Learning Outcomes (PLOs) revealed a significant gap between the programme’s stated goals and the skills identified as critical by external benchmarks such as the QAA (2023) and the World Economic Forum (2023),

particularly regarding AI literacy, advanced data analytics, and sustainability. This highlights the tendency for PLOs to lag behind the rapid pace of industry change and reinforces the necessity of regular, benchmark-driven review. Secondly, the diagnostic analysis of the programme's structure identified a crucial tension between strong *vertical coherence*, where concepts are effectively scaffolded within subject silos, and a weaker *horizontal coherence*, where the integration of transferable skills across different modules is not systematic. This finding gives credence to the literature that warns against curricula functioning as a collection of discrete topics rather than an integrated whole (Harden, 2001; Kopera-Frye et al., 2008). Finally, the analysis of AI integration revealed that its treatment as an isolated topic, rather than an infused, cross-curricular competency, fails to prepare students for a workplace where AI is a ubiquitous tool. These findings collectively demonstrate that even a well-intentioned, contemporary curriculum can suffer from structural weaknesses that are only made visible through a holistic mapping process.

Implications of the Study

The findings and the framework itself carry significant implications for curriculum governance, pedagogical practice, and institutional strategy within higher education.

For **curriculum governance and leadership**, this study demonstrates that curriculum mapping, when properly implemented, is a powerful tool for academic leadership. It provides a structured and evidence-based mechanism for fostering the “collaborative dialogue” and “community of practice” that the literature identifies as essential for overcoming faculty resistance and achieving meaningful, sustainable change (Joyner, 2016b; Archambault & Masunaga, 2015). It moves curriculum review from a potentially contentious, opinion-based debate to a data-informed, professional conversation focused on the collective student experience. For an institution like Arden, with its geographically dispersed faculty, the map becomes an essential shared artefact that builds a sense of team ownership and overcomes the “smoke-stack syndrome” that can plague academic departments (Saad, 2014).

For **pedagogical practice**, the implications are profound, particularly concerning assessment in the age of AI. The study's recommendations for “AI-aware” assessments push faculty and institutions to move beyond a defensive posture of trying to prevent academic misconduct towards a proactive stance of redesigning assessments to measure the higher-order skills of critical evaluation, ethical judgment, and metacognition. This requires a fundamental shift in how learning is measured, directly aligning with the principles of constructive alignment (Biggs, 2003; Livingstone, 2014) by ensuring that if we intend for students to learn to work *with* AI, our assessments must be designed to measure their ability to do so effectively and ethically.

For **institutional strategy**, this research shows that adopting a systematic mapping process is not just an operational tactic but a strategic act. For a university like Arden, it provides tangible evidence to support its brand identity as “progressive” and “innovative.” It allows the institution to demonstrate to students, employers, and accreditation bodies like the QAA and foreign bodies such as the AACSB that its curriculum is intentionally designed and dynamically managed to produce genuinely work-ready graduates. In a competitive market, such demonstrable coherence and relevance is a powerful differentiator.

Limitations of the Study

As a scholarly work, it is important to acknowledge the limitations of this study. The primary limitation is its conceptual and documentary nature. The application of the

framework was a conceptual analysis based on publicly available documents representing the “written” or “intended” curriculum. It cannot, therefore, make definitive claims about the “enacted” curriculum (what actually happens in the virtual classroom) or the “learned” curriculum (what students actually take away from their experience) (Kopera-Frye et al., 2008; Arafeh, 2016). A full empirical study would require triangulation with other data sources, such as classroom observations, student focus groups, and analysis of student work.

Secondly, as a **single-case study**, the specific findings related to the Arden University programme are not statistically generalisable to other institutions. The purpose of a case study, however, is not statistical generalisation but “analytical generalisation,” where the goal is to expand and generalise theories (Yin, 2018). While the specific diagnosis is unique to Arden, the framework, the methodological process, and the types of issues identified (e.g., the tension between vertical and horizontal coherence) are designed to be highly transferable to other higher education institutions, particularly those operating in a digital-first environment.

Future Directions for Research and Practice

The findings and limitations of this paper point toward several critical directions for future research and practice in the field of curriculum mapping and design.

The most immediate next step is the **empirical validation** of the proposed framework. Future research should apply this framework in a real-world setting, such as Arden University, and conduct a longitudinal study to measure the impact of the resulting curriculum changes. Such a study could use pre- and post-intervention data to measure shifts in student performance, engagement, retention rates, and perceptions of their learning journey (Bull, 2025; Joyner, 2016b). This would provide the empirical evidence needed to move the framework from a theoretical model to a proven tool for enhancement.

A second, exciting avenue for future research lies in “**smart**” **curriculum mapping**. As discussed by Alam and Benaida (2022), the integration of AI into the mapping process itself holds significant potential. Future studies could investigate the development and efficacy of AI-powered tools that could automate parts of the data collection and analysis, provide real-time data visualisations of curriculum coherence, and even use predictive analytics to model the potential impact of proposed curriculum changes.

Thirdly, future research could conduct **cross-disciplinary and cross-institutional studies**. Applying this framework to different disciplines within the same institution would provide valuable insights into the variations in mapping approaches and purposes, as noted by Rawle et al. (2017). Furthermore, comparative case studies between different types of institutions (e.g., digital-first vs. traditional campus-based) would help to understand how institutional context shapes the challenges and successes of curriculum mapping initiatives.

Finally, future practice should explore the role of **student co-creation** within the curriculum mapping process. The current model positions students primarily as a source of feedback data. A more radical, student-centred approach would involve students as active partners in the mapping and design process, giving them a voice in shaping their own educational journey. Research into the methodologies and impact of such a co-creative approach would be a valuable contribution to the literature on student-centred learning (Livingstone, 2014).

In conclusion, this paper has sought to contribute by synthesising a comprehensive, theoretically grounded, and practical framework for curriculum mapping in the digital age. In a world of constant disruption, a curriculum that is intentionally designed, transparently structured, and dynamically reviewed is arguably the most powerful tool a university has to prepare its students for a future that is complex and uncertain.

Declarations

Conflict of Interest

The author also declares no conflicts of interest in the preparation or publication of this manuscript.

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Predicting Online Instructional Design Students’ Intention to Use AI Tools: Value, Utility, and Self-Efficacy

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Abstract

This study examined online instructional design (ID) students’ intention to use AI tools in their practice. Seventy-four online ID master’s students in the United States participated. Regression analysis showed demographic variables (gender, age, full-time status) were not related to their intention to use AI tools in practice. However, students’ value of AI tools for learning, utility for their own academic tasks, and self-efficacy were significantly related to their intention. Cluster analysis revealed two distinct groups: one scored above average on value, utility, self-efficacy, and intention to use AI tools while the other scored below average on these measures. Content analysis revealed diverse perspectives between groups on AI tool use, perceptions of AI in education, and necessary training for AI tools in ID. Findings inform practical guidance for training ID students.

Keywords: Instructional design students, artificial intelligence, intention to use AI tools in instructional design, instructional design with AI

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Artificial intelligence (AI) refers to the capacity of computer systems, developed through large-scale machine learning, to perform tasks typically requiring human intelligence (Akgun & Greenhow, 2022). Generative AI tools, which are specific examples of AI, include but are not limited to content and editing as well as generating and data analysis AI (e.g., ChatGPT, Gemini, Copilot), image editing and generating AI (e.g., DALL.E, or Canva AI), or sound generating and editing AI (e.g., AIVA).

These AI tools possess considerable potential for use in instructional design (ID) practice. For example, AI tools can generate problems and scenarios in problem-based and case-based learning contexts (Silapachote & Srisuphab, 2017). In the realm of assessment, AI tools can score students' assignments, generate diagnostic feedback, and predict learner performance based on behavioral data. They also allow for automated grading, reduction of human bias in assessment, and delivery of personalized feedback to learners (Owan et al., 2023). In terms of task analysis, AI tools can chunk information with appropriate learning objectives, aligning tasks with learners' prior knowledge and real-world context (Lin et al., 2021).

Many educators in the ID field have argued that future instructional designers' effective use of AI tools may help them do their jobs much more efficiently and effectively (Owan et al., 2023); however, not every student willingly intends to use AI tools for various reasons, such as ethical concerns, lack of transparency, and data privacy issues (Owan et al., 2023; Park et al., 2026; Shehata et al., 2026; Weng et al., 2024). Examining why ID students use AI tools in the ID process is crucial because they are likely to adopt these tools in the real ID field after graduation.

Despite the importance of ID students' perspectives, little empirical research has been conducted. Luo et al. (2025) investigated instructional designers' perceptions and experiences using generative AI across various design tasks. They found that generative AI was commonly used for brainstorming, handling low-stakes tasks, streamlining processes, and enhancing collaboration. Similarly, Parsons and Curry (2024) examined whether ChatGPT could complete graduate-level ID assignments, such as learner needs, tasks, and analyses. They found that ChatGPT could generate acceptable drafts but proved inadequate for contextual specificity, citation formatting, and deeper customization.

The ID field is rapidly evolving with the emergence of new AI tools and using them in the ID process is essential for effective instruction design (Luo et al., 2025). Thus, understanding what motivates students to use AI tools in ID practice is very important. The purpose of the study is, therefore, to investigate factors related to ID students' intention to use AI tools in ID practice.

Theoretical Framework

The Technology Acceptance Model (TAM) developed by Davis (1989) provides a foundational framework for understanding users' adoption of new technologies. TAM posits

that two primary constructs—perceived usefulness and perceived ease of use—determine users’ behavioral intention to adopt a given technology. Perceived usefulness refers to the degree to which individuals believe that using a technology will enhance their performance, while perceived ease of use reflects the extent to which users perceive the technology as free from effort. Over the past three decades, TAM has been extensively applied and extended across diverse technological and educational contexts, demonstrating robust predictive validity for technology adoption behaviors (Scherer et al., 2019; Venkatesh et al., 2003).

Building on this body of research, the current study extends TAM to examine instructional design students’ intentions to use AI tools in their professional practice. Recognizing the multifaceted nature of AI’s potential benefits in educational contexts, we reconceptualized perceived usefulness through two distinct constructs: the value of AI tools for student learning, which captures beliefs about AI’s broader pedagogical benefits, and the utility of AI tools for personal academic tasks, which reflects perceptions of AI’s practical benefits for one’s own academic work. This differentiation allows for a more fine-grained understanding of how various dimensions of usefulness may differentially influence adoption intentions.

Furthermore, given that generative AI tools employ natural language interfaces that minimize traditional usability barriers, we did not include perceived ease of use as a separate variable. Instead, we incorporated self-efficacy in using AI tools as a predictor variable. This decision is supported by extensive research demonstrating that self-efficacy serves as a critical variable in technology acceptance among educators (Park et al., 2026; Scherer et al., 2019). A recent meta-analysis on AI adoption in education identified self-efficacy as a significant factor influencing teachers’ adoption of AI (McGehee, 2024). In addition, self-efficacy has been established as one of the most used predictors of technology acceptance in educational settings, with a direct and positive influence on behavioral intention to use various educational technologies (Granić, 2022). While this relationship has been well documented among preservice and in-service teachers, less research has examined AI acceptance in ID practice among instructional design students. The current study addresses this gap by applying an extended TAM framework to this understudied population.

Social Demographic Information

Social demographic variables such as gender, age, and student status (full-time vs. part-time) may influence students’ intention to use AI tools in ID practice. Gender appears relevant to AI adoption intention. Studies show male students report higher adoption intentions than female students (Al Omari et al., 2024); however, this pattern is inconsistent. For example, K. Y. Lee (2021) reported no significant gender differences. Age effects also remain inconclusive. Some studies show older students demonstrate stronger intention to use AI tools, suggesting a positive age-adoption relationship (Al Omari et al., 2024), while others found no significant association (K. Y. Lee et al., 2021). Although student status has received limited attention in previous research, it may be a predictable factor. We anticipated that full-time students may have more exposure to GenAI tools, leading to greater use of AI tools in ID practice (K. Y. Lee et al., 2021).

Value of AI Tools for Student Learning

Value of AI tools for student learning refers to the perceived value of AI integration to enhance student learning. Effective integration depends on aligning AI capabilities with instructional goals and pedagogical strategies (Moundridou et al., 2024). Research highlights AI's substantial potential to enrich learning through personalized instruction, automated educational tasks, and improved instructional effectiveness. AI has been employed to develop tailored assessments, generate teaching resources, and provide adaptive learning environments that enhance student engagement and comprehension (Chen & Wu, 2024). In student-centered environments, AI tools can personalize instruction, adapt assessments, and act as a tutor, facilitator, or assistant (Park & Doo, 2024). Integration of AI in student learning occurs when instructional designers and educators recognize their value (Luo et al., 2025).

Utility of AI Tools for Personal Academic Tasks

Utility of AI tools for personal academic tasks refers to students' perceived usefulness of AI tools to enhance their productivity, efficiency, and insight generation in academic tasks based on personal experiences. Current research highlights three main benefits for using AI. First, AI tools enhance personalized learning by providing tailored content and feedback. For example, ChatGPT supports students in writing and reading tasks by helping structure essays, generate ideas, and develop customized study materials (Trust et al., 2023). Second, AI technologies enable efficient task management by automating repetitive tasks, such as designing quizzes, discussion prompts, rubrics, and scenario-based assessments, freeing students to focus on higher-order thinking and critical analysis (Bolick & da Silva, 2024; Luo et al., 2025). Third, AI tools facilitate effective academic communication through automated grading and real-time personalized feedback, helping students understand their performance and manage their academic progress (Moundridou et al., 2024). When ID students see tangible benefits to their academic productivity, they are more likely to use AI tools in ID practice.

Self-Efficacy in Using AI Tools

Self-efficacy in using AI tools refers to students' confidence in their ability to effectively use AI tools in ID contexts. Higher self-efficacy leads to increased engagement and greater perceived usefulness of AI tools (Hong, 2022; Park et al., 2026; Zimmerman, 2000). Research shows instructional designers' self-efficacy in technology integration, including AI tools, significantly predicts their actual use of these technologies in practice (Y. Lee & Lee, 2014). Instructional designers with higher self-efficacy are more likely to persist through technological challenges, incorporate innovative tools, and adopt learner-centered approaches (Anderson et al., 2011). Self-efficacy is particularly crucial for instructional designers because their roles involve both adopting technology and facilitating its effective use for others. ID students with high self-efficacy in using AI tools are more likely to use them in practice.

Research Questions

This study examined the factors that explain instructional design online graduate students' intentions to use AI tools in ID practice. Through a review of the literature, we identified the following factors: sociodemographic characteristics (i.e., gender, age, and student full-time

status), value of AI tools for student learning, utility of AI tools for personal academic tasks, and self-efficacy in using AI tools. Two research questions guided the study:

1. What factors predict ID students' intention to use AI tools in their ID practice?
2. What are ID students' experiences, perspectives, and training needs regarding AI tools?

Methods

Research Contexts and Participants

This research was conducted in an online graduate course required for the ID master's program at a university in the United States. The course consists of six modules, each introducing an emerging technology (e.g., artificial intelligence). Each module lasts two or three weeks, during which ID students explore diverse AI tools, such as image generation, sound editing, and comprehensive tools (e.g., ChatGPT, Gemini, Copilot). Based on guided practice with the introduced AI tools and extra effort, ID students created a plan for integrating them into a specific content domain of their interest to enhance learning and teaching practices. Two sections of the course are offered in fall every year. We collected data from both sections over a two year period.

A total of 74 ID students participated in the study, including 40 men (54.1%) and 34 women (45.9%) with an average age of 37.29 ($SD = 9.75$). The majority identified as White ($n = 34$; 45.9%), followed by Hispanic or Latino ($n = 13$; 17.6%), Asian ($n = 13$; 17.6%), Black or African American ($n = 11$; 14.9%), and two or more races ($n = 3$; 4.1%). Most participants were full-time students ($n = 52$; 70.3%). At the start of the study, 82.4% of the ID students ($n = 61$) reported prior experience with AI tools, mostly ChatGPT and Google Gemini; 17.6% of the students ($n = 13$) had no prior experience with AI tools.

Measurements

We developed and administered to ID students an online three-part survey called AI Tools in ID, which included (a) demographic information and prior experience with AI tools; (b) four variables: the value of AI tools for student learning, the utility of AI tools in personal academic tasks, self-efficacy in using AI tools, and intention to use AI tools in ID practice; and (c) three open-ended questions. A 5-point Likert scale was employed for all four variables, ranging from 1 (strongly disagree) to 5 (strongly agree). More detailed information about each scale appears below.

First, the value of AI tools for student learning, adapted from Chan and Hu (2023), consisted of three items, for example, "I think integrating AI tools like ChatGPT into learning contexts will be helpful." Cronbach's alpha with our participants in the study was .845.

Second, the utility of AI tools in personal academic tasks adapted from Chan and Hu (2023) consisted of three items, such as "I believe that AI tools can assist me in doing my academic work more efficiently." Cronbach's alpha with our participants was .857.

Third, self-efficacy in using AI tools was created following Bandura's (2006) guidelines. We used three items, for example, "I feel confident using an AI tool to complete my tasks." Cronbach's alpha with our participants was .835.

Fourth, intention to use AI tools in ID practice included four items, adapted from An et al., (2023). An example is "I intend to use an AI tool in my ID activities." Cronbach's alpha with our participants was .861.

Last, three open-ended questions were created to examine ID students' experiences, perspectives, and training needs on AI tools:

- (a) How did you use the AI tools most in the ID assignment?
- (b) How has your overall experience with AI Chatbots influenced your perspective on AI and its role in instructional design and technology?
- (c) What kinds of training are necessary to help instructional designers do well in their jobs in the emergence of AI tools?

Procedures

The Institutional Review Board on the campus where we conducted the study approved the research. We administered the online survey to ID students once they completed the AI module and read and signed the online consent form. Participation in the research was 100% voluntary. Of the 81 enrolled students, 74 participated at a rate of 91.36%. We provided no incentives and imposed no penalties for student survey participation or nonparticipation.

Results

Factors Predicting ID Students' Intention to Use AI Tools in ID Practice

Table 1 provides a summary of participants' responses regarding the value of AI tools for student learning, utility of AI tools for personal academic tasks, self-efficacy in using AI tools, and intention to use AI tools in ID practice. We used a 5-point Likert scale, with higher scores indicating stronger agreement. Among the four measured variables, the value of AI tools for student learning garnered the highest overall agreement ($M = 3.90$, $SD = 0.75$), followed by the utility of AI tools for personal academic tasks ($M = 3.76$, $SD = 0.81$), self-efficacy in using AI tools ($M = 3.51$, $SD = 0.86$), and intention to use AI tools in ID practice ($M = 3.42$, $SD = 0.84$). For details on each factor and item, see Table 1.

Table 1*Mean and Standard Deviation of Study Variables*

Dimension of Scales	<i>M</i>	<i>SD</i>
Value of AI tools for student learning ($\alpha = .845$)	3.90	0.75
I think integrating AI tools like ChatGPT into learning contexts will be helpful.	3.88	0.88
I agree with the idea that integrating AI tools into the design of learning activities will benefit students' learning.	3.93	0.88
The AI tools integrated into learning activities can assist students in attaining learning outcomes more efficiently.	3.88	0.83
Utility of AI tools for personal academic tasks ($\alpha = .857$)	3.76	0.81
I believe that AI tools can assist me in doing my academic work more efficiently.	3.73	0.94
I believe by utilizing AI tools, I can generate more unique insights and perspectives that I may not have thought of myself.	3.72	0.96
I think AI tools can provide me with personalized and immediate feedback and suggestions for my assignments.	3.82	0.87
Self-efficacy in using AI tools ($\alpha = .835$)	3.51	0.86
I feel confident using an AI tool to complete my tasks.	3.46	1.09
I believe I have the necessary skills to work with an AI tool.	3.80	0.79
I am confident in my ability to use AI tools and apply their solutions.	3.28	1.08
Intention to use AI tools in ID practice ($\alpha = .861$)	3.42	0.84
I intend to use an AI tool in my ID activities.	3.55	0.98
I would recommend my colleagues use an AI tool for their ID tasks.	3.50	0.98
Given certain circumstances, I would utilize an AI tool for doing my ID.	3.50	1.02
I will actively seek out opportunities to integrate AI tools into the ID process.	3.11	1.03

Note. Responses were recorded on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

We conducted Pearson correlation analysis to examine relationships among social demographic factors and key study variables (see Table 2), coding social demographic variables as follows: gender (1 = man, 2 = woman), age (1 = under 40, 2 = 40 or older), and student status (1 = full-time student, 2 = part-time student).

Table 2*Descriptive Statistics and Bivariate Correlations Among Study Variables (N = 74)*

	<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7
1. Gender	1.46	0.50	1						
2. Age	1.51	0.50	-.217	1					
3. Student status	1.30	0.46	.290*	-.134	1				
4. Value of AI tools for student learning	3.90	0.75	-.150	.115	.090	1			

5. Utility of AI Tools for personal academic tasks	3.76	0.81	-.237*	.187	.245*	.670***	1
6. Self-efficacy in using AI tools	3.51	0.86	-.046	-.231	.242*	.647***	.622*** 1
7. Intention to use AI tools in ID practice	3.42	0.84	-.061	-.093	.127	.718***	.702*** .700*** 1

Note. * $p < .05$, *** $p < .001$.

Pearson correlation analysis showed that students' gender ($r = -.061, p > .05$), age ($r = -.093, p > .05$), and full-time status ($r = .127, p > .05$) were not statistically correlated with the use of AI tools in ID practice. The value of AI tools for student learning ($r = .718, p < .001$), the utility of AI tools for personal academic tasks ($r = .702, p < .001$), and self-efficacy in using AI tools ($r = .700, p < .001$), however, were positively correlated with the intention to use AI tools in ID practice.

To examine the effects of combined variables like social demographic factors and the three identified variables on the intention to use AI tools in ID practice, we conducted a hierarchical regression analysis (shown in Table 3). We entered social demographic variables (gender, age, and full-time status) in Step 1. The results showed that social demographic variables did not significantly predict ID students' intention to use AI tools in ID practice, $F(3, 70) = 0.827, p > .05$.

In Step 2, we entered the three identified variables: the value of integrating AI tools for student learning, the utility of AI tools for personal academic tasks, and self-efficacy in using AI tools. The results revealed that the three added variables significantly improved the model (F change = 44.453, $p < .001$) and increased the explained variance to 64.8% (Adjusted $R^2 = .648$). Among these, the utility of AI tools for personal academic tasks ($\beta = .397, t = 3.628, p < .001$) most significantly contributed to the model followed by the value of AI tools for student learning ($\beta = .331, t = 3.164, p < .01$) and self-efficacy in using AI tools ($\beta = .243, t = 2.259, p < .05$). The results indicated ID students' perceived utility of AI tools while doing their own academic tasks is more important than the general value of AI tools for student learning, showing the importance of using diverse AI tools and experiencing its benefits for personal academic tasks.

Table 3

Model Summaries for Hierarchical Regression Analysis Predicting Intention to Use AI Tools in ID (N = 74)

	Step 1			Step 2		
	B	SE	β	B	SE	β
Step 1						
Gender	-.207	.210	-.123	.167	.131	.099
Age	-.155	.209	-.089	-.207	.137	-.119

Student Status	.277	.226	.151	-.189	.144	-.103
Step 2						
Value of AI tools for student learning				.370	.117	.331**
Utility of AI tools for personal academic tasks				.412	.113	.397***
Self-efficacy in using AI tools				.237	.105	.243*
Model Summary						
R^2	.034			.677		
Adjusted R^2	-.007			.648		
F for R^2 change	.827			44.453***		

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

ID Students' Experiences, Perspectives, and Training Needs

We performed a non-hierarchical k-means cluster analysis to determine the optimal number of clusters representing the data set. After testing multiple cluster solutions, we chose the two-cluster solution, which provided a clear division between participants with low and high perspectives on AI tools. In addition, the three-cluster and four-cluster solutions had very small groups in each cluster, making comparisons difficult.

Table 4 presents the descriptive statistics for the two clusters on AI tools in ID. The values of each construct were standardized from 0 to 1, where a positive number meant above the mean and a negative number meant below the mean. Cluster 1 ($n = 41$, 55.4%) had scores on all variables above the mean. These participants perceived AI tools as highly valuable for student learning ($M = 4.32$, $SD = 0.47$, $z = 0.56$) and saw the utility of AI tools for personal academic tasks ($M = 4.25$, $SD = 0.45$, $z = 0.61$). They also reported higher self-efficacy in using AI tools ($M = 4.03$, $SD = 0.59$, $z = 0.61$) and higher intention to use AI tools in ID practice ($M = 3.94$, $SD = 0.58$, $z = 0.62$) than the mean, zero in this case. This group was identified as a highly positive group.

Table 4

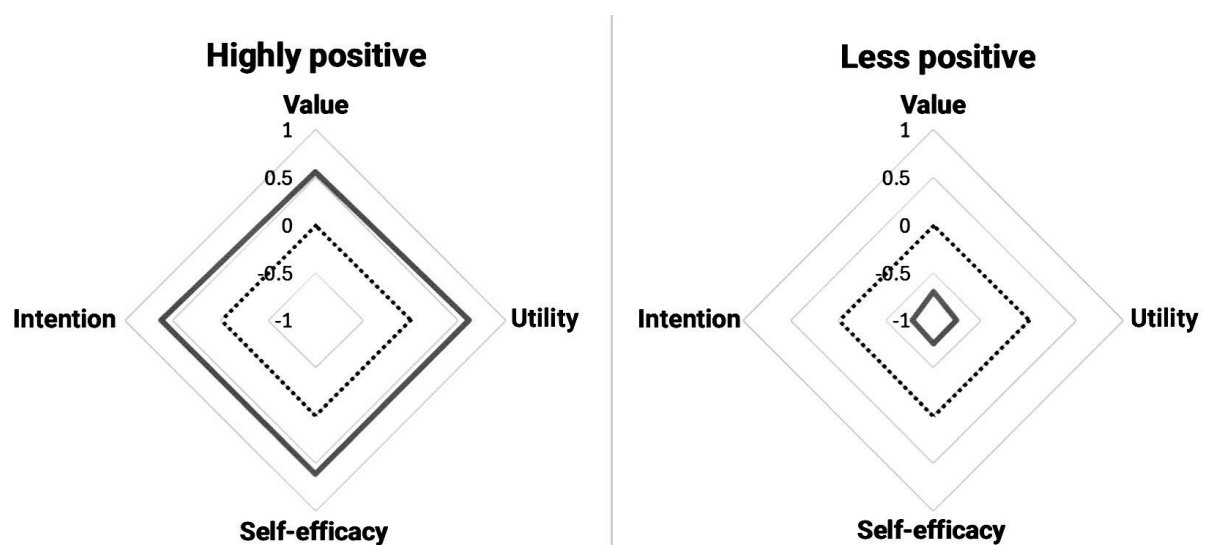
Descriptive Statistics for Two Perspective Clusters on AI (N = 74)

Perspectives on AI	Cluster 1 ($n = 41$, 55.4%)			Cluster 2 ($n = 33$, 44.6%)		
	M	SD	z	M	SD	z
Value of AI tools for student learning	4.32	0.47	0.56	3.37	0.72	-0.70
Utility of AI tools in personal academic tasks	4.25	0.45	0.61	3.14	0.74	-0.76
Self-efficacy in using AI tools	4.03	0.59	0.61	2.87	0.70	-0.75
Intention to use AI tools in ID	3.94	0.58	0.62	2.77	0.64	-0.78

Cluster 2 ($n = 33$, 44.6%) had scores on all variables below the mean. These participants valued AI tools less for student learning ($M = 3.37$, $SD = 0.72$, $z = -0.70$) and saw less utility in their own academic tasks ($M = 3.14$, $SD = 0.74$, $z = -0.76$). In addition, they reported lower self-efficacy in using AI tools ($M = 2.87$, $SD = 0.70$, $z = -0.75$) and a lower intention to use AI tools in ID practice ($M = 2.77$, $SD = 0.64$, $z = -0.78$) than the mean. This group was classified as a less positive group. Figure 1 illustrates the differences between the two clusters using z-scores, showing how each group deviated from zero across the four variables.

Figure 1

Profiles of ID Students' Perspectives on AI Tools



Note. Value = Value of AI tools for student learning, Utility = Utility of AI tools for personal academic tasks, Self-efficacy = Self-efficacy in using AI tools, Intention = Intention to use AI tools in ID practice.

Content Analysis

To further understand how ID students in each cluster viewed AI tools, we conducted a qualitative content analysis (Schreier, 2012), examining answers to each question separately. Qualitative content analysis is a systematic approach to analyzing textual data that involves developing categories to describe the meaning of qualitative material while also allowing for the quantification of category frequencies (Schreier, 2012). In the content analysis of the 219 responses, the two authors followed a systematic coding process. The unit of analysis was conveyed meaning. When participants expressed multiple ideas in a sentence, we assigned the response multiple codes accordingly. First, each author independently reviewed all open-ended responses to become familiar with the data and developed an initial codebook. Second, both authors met to compare their initial codebooks and reached consensus on a preliminary coding scheme. Third, using the preliminary coding scheme, each author independently coded all responses, followed by discussion to refine the codebook iteratively. Fourth, using the finalized codebook, we recoded all responses independently and

achieved an intercoder reliability of 91%. Fifth, we resolved the remaining discrepancies through discussion until reaching full agreement.

Tables 5, 6, and 7 present a content analysis of open-ended responses grouped into themes. Results appear as frequencies by clusters. The analysis identifies differences in the use of AI tools, perceptions of AI tools in ID, and the necessary training to learn AI tools in ID.

Primary Uses of AI Tools for ID Assignments

ID students used AI tools for diverse purposes, such as content drafting, data analysis, grammar assistance, idea generation, and logic checking (see Table 5). The highly positive group reported more engagement with AI tools than the less positive group. For example, more students in the highly positive group mentioned grammar assistance and idea generation. These comparisons suggest students in the highly positive group utilized AI tools more frequently in their ID assignments.

Table 5

ID Students' Primary Uses of AI Tools for ID Assignments by Cluster

Theme	Category	Definition	Sample Comment	Frequency	
				Highly positive	Less positive
Primary uses of AI tools for ID assignments	Content drafting	Using AI to help draft, outline, or summarize content	They do a good job of compiling content from multiple sources into one location/document.	15	12
	Data analysis	Using AI to analyze or process data for insights	Google Gemini aided in data analysis, enabling me to draw valuable conclusions.	0	1
	Grammar assistance	Using AI for grammar checking, proofreading, or editing	I use it to modify my article grammar and generate some ideas.	13	7
	Idea generation	Using AI to brainstorm, inspire, or generate new ideas	Generates content quickly although we can debate on the quality of content.	24	10

Logic checking	Using AI to verify reasoning and logic	I used AI tools to do logic check, get information on a topic, confirm information or to create an essay.	1	0

Perceptions of AI in ID

Three themes emerged describing ID students' perceptions of AI in ID: attitudes, instructional impact, and challenges (see Table 6). Students showed three attitude types: positive, hesitant, and negative. Students in the highly positive group showed more positive orientation, whereas those in the less positive group showed more cautious attitudes. Regarding instructional impact, students in the highly positive group viewed AI as a partner—a supportive resource for instruction or learning that enhanced their efficiency and facilitated idea generation—more than those in the less positive group. Some students mentioned challenges, including accuracy issues, ethical concerns, and risk of overreliance on AI tools.

Table 6

ID Students' Perceptions of AI in Education by Cluster

Category	Code	Definition	Sample Comment	Frequency	
				Highly positive	Less positive
Attitudes	Positive orientation	Expressing either a shift toward positive attitudes or direct positive views and acceptance of AI	I was completely against its use in a learning environment, but through the readings and activities in class, I decided to try it and its advantages are undeniable.	21	7
	Hesitant view	Expressing uncertainty, skepticism, or lack of confidence about AI	I have yet to use AI for ID as I still am skeptical.	2	6
	Negative concern	Expressing mistrust, resistance, or rejection of AI	I believe it might be able to help with figuring out possible	1	5

			problems, but since the problem is human-related, I do not think it will understand the true problem.		
Instructional impact	Supportive resource	Using AI as a supportive resource for instruction or learning	These tools have become invaluable allies in personalizing learning, providing immediate support, and enhancing engagement.	12	3
	Efficiency	Viewing AI as a tool that improves efficiency or saves time	I think AI tools will have a major impact on ID as the tools can provide lesson/learning objectives within seconds.	6	1
	Idea generation	Seeing AI as a tool that enhances idea generation	It's a great tool to help generate creative ideas. I view their suggestions as a baseline to creating instructional strategies.	14	4
Challenges	Accuracy issue	Having concerns about the factual accuracy or reliability of AI outputs	From my little experience, the AI is limited in its ability to source meaningful content and filter for inaccuracies.	1	3
	Ethical concerns	Mentioning ethical issues, plagiarism, or responsible AI use	Thoughtful implementation, respecting privacy, and ethical considerations is essential in realizing their educational potential.	0	1
	Overreliance risk	Worrying about relying too much on AI replacing human effort	The only thing we could do is to ensure that they use these tools wisely, avoiding overuse or misuse.	1	0

Necessary Training to Learn AI Tools in ID

Students proposed three training approaches for learning AI tools in ID: ID program-level training, hands-on professional development (PD), and ethical guidance (see Table 7). For program-level training, students in the highly positive group emphasized basic AI literacy more than those in the less positive group, including fundamental and conceptual knowledge, integration into ID practice, and advanced courses to effectively utilize AI tools. For hands-on PD, students suggested three areas: tool training, prompting skills, and applied skills in real ID projects. For ethical guidance, students emphasized training on bias awareness and academic integrity issues.

Table 7

Necessary Training to Learn AI Tools in ID

Category	Code	Definition	Sample Comment	Frequency	
				Highly positive	Less positive
ID program-level training	Basic literacy	Learning fundamental AI knowledge and concepts	First of all, IDers need to have fundamental knowledge about AI and how it works.	7	2
	Advanced course	Studying AI through advanced or specialized academic courses	I personally seek out a variety of free and paid certifications.	4	1
	Design methods	Integrating AI into ID methods and curriculum	A workshop of helping IDer building their own tools for their specific need would be helpful.	11	2
Hands-on PD	Tool training	Hands-on training in specific AI tools such as ChatGPT	IDs should have hands-on experience using AI, and there are already so many AI tools out there that it would be helpful to have specific training on the most helpful tools.	8	4
	Prompting skills	Developing skills to write and refine	Training is needed on how to develop good tools prompts and how	9	7

		effective prompts	to finesse the tools to developing the desired outputs.		
	Applied practice	Practical examples and training for applying AI in real ID	Certainly, a course that provides examples and practice using AI to generate and edit content appropriately would be helpful.	4	7
Ethical Guidance	Bias awareness	Recognizing AI bias, fairness issues, and limitations	Another type of training that would be beneficial to IDers and instructional technologists would be learning to identify bias, protect learners' data, and incorporate critical learning activities using AI.	7	4
	Academic integrity issues	Addressing ethics, plagiarism, and responsible use of AI	I would say that a training on ethical issues when using AI tools is necessary to avoid plagiarism.	6	2

Discussion

This study examined factors determining ID students' intention to use AI tools in their practice. Social demographic information was not a statistically meaningful predictor; however, value of AI tools for student learning, utility for personal academic tasks, and self-efficacy were strong and significant predictors. Cluster analysis identified two distinct groups, with highly positive students reporting higher scores across all variables than their less positive counterparts.

Contrary to our hypothesis, background factors like age, gender, and full-time student status did not contribute to the model statistically. This finding aligns with earlier studies showing that user characteristics mattered less than how users valued and perceived the tool's usefulness. For example, Venkatesh et al. (2003) found that age and gender had only a small effect on technology use, especially when people's views on usefulness and ease of use were considered. Teeroovengadam et al. (2017) also showed that demographic factors had no clear impact on students' decision to adopt a new technology. These results reinforce that students' intention to use AI tools is shaped more by how they appraise the tools than by who they are.

This study contributes to the technology acceptance literature by demonstrating the value of differentiating perceived usefulness into distinct constructs when examining AI tool adoption. While the original TAM treats perceived usefulness as a unitary construct, our extended framework distinguished between the value of AI tools for student learning and the utility of AI tools for personal academic tasks. The hierarchical regression results revealed that this differentiation captured meaningful variance in behavioral intention: utility for personal academic tasks emerged as the strongest predictor ($\beta = .397$), followed by value for student learning ($\beta = .331$). This finding suggests that for instructional design students, direct, hands-on experience with AI tools for their own work carries greater predictive weight than general beliefs about AI's pedagogical benefits. This pattern echoes Davis's (1989) original proposition that perceived usefulness drives technology acceptance, while extending it to show that personal, task-specific utility may be more motivating than abstract pedagogical value.

Our framework also replaced perceived ease of use with self-efficacy, which proved appropriate for generative AI contexts. Self-efficacy significantly predicted intention ($\beta = .243$) in a technology environment where natural language interfaces minimize traditional usability barriers. The strong predictive role of self-efficacy aligns with social cognitive theory (Bandura, 1986), which identifies self-efficacy as a central driver of motivation and action. When students felt confident in their ability to engage with AI tools, they were more likely to view them as manageable and worthwhile, thereby increasing their intention to use them in practice (Park et al., 2026). Overall, the extended model explained 64.8% of variance in intention—comparable to or exceeding explanatory power reported in TAM meta-analyses (Scherer et al., 2019)—while offering a more fine-grained understanding of the distinct pathways through which AI tool perceptions influence adoption intentions among future instructional design professionals.

The cluster analysis further highlighted how students differed in their overall orientation toward AI tools. Students in the highly positive group scored above average on all measured variables. They were more likely to recognize AI's value for student learning and its utility for personal academic tasks and expressed a stronger intention to apply it in their ID practice. This aligns with findings from prior studies showing that satisfaction and trust formed through AI interactions significantly predicted future adoption (Wang & Li, 2024). The qualitative responses reinforced this pattern: students with positive views of AI tools tended to describe using AI in diverse ways and generated more constructive ideas, whereas those with less positive views were more reserved in how they envisioned using AI tools in ID practice. In sum, our study shows the importance of ID students' views on AI tools in shaping their intention to use them in ID practice. These findings carry practical implications for how ID programs can prepare students to work effectively with AI tools.

Practical Guidance to Enhance ID Students' AI Literacy

Our findings suggest several practical recommendations to enhance students' effective use of AI tools in ID practice.

Strengthen Personal Utilization of AI Tools Through Course Integration

Our findings show students were more likely to engage with AI tools directly connected to their personal academic tasks and coursework. Integrating AI tools into tasks and learning can enhance students' engagement by making the tools more relevant and meaningful to their academic experience (Chan & Hu, 2023; Chen & Wu, 2024). We suggest instructors in ID courses encourage meaningful AI use by integrating the tools into course activities—for example, idea development, feedback, or peer review—while also offering them as optional resources to support student autonomy (Ursavaş et al., 2025).

Help Students Recognize AI's Value for Future Learners

The value students placed on AI tools for student learning was the second-strongest predictor of intention, suggesting that students who understood AI's pedagogical potential were more motivated to incorporate it into their practice. Instructors can foster this recognition by discussing how AI can personalize feedback, support diverse learners, or scaffold complex tasks. Case studies demonstrating successful AI integration in K-12 or higher education contexts may help students envision AI's benefits beyond their own coursework and see themselves as designers who can leverage AI to enhance learning outcomes.

Enhance Students' Self-Efficacy in Using AI Tools

Students with higher self-efficacy were more confident and proactive in using AI tools for ID tasks. Their intention to use AI was significantly explained by self-efficacy beliefs (Park et al., 2026). To build self-efficacy, instructors should design scaffolded, low-stakes AI tasks that offer repeated, successful experiences across a range of design contexts. Training sessions focused on prompt engineering and tool functionality can also strengthen students' confidence in AI usage (Woo et al., 2024), as ID students indicated (see Table 7). Through structured practice, students will feel motivated and capable of using them independently.

Provide Hands-On Opportunities to Learn AI Tools in ID Courses or Programs

Many students expressed a need for more AI training, either through a dedicated course or regular class activities. At the program level, offering an integrated course can provide students with foundational AI concepts, ethical frameworks, and hands-on experience through dedicated sessions (Hopson et al., 2025). At the course level, AI tools can be embedded into activities like brainstorming, refining ideas, or evaluating sources to support critical thinking (Boyle, 2025). This dual approach supports students with varying experience levels by combining foundational understanding with applied practice in authentic ID tasks.

Provide Ethical Guidance on How to Use AI Tools in ID Practice

Students were eager to use AI tools but remained uncertain about their ethical implications in academic and professional settings. Key concerns included data privacy, informed consent, and algorithmic bias, highlighting the need for clear ethical guidance. To promote responsible AI use in ID, instructors should integrate ethical considerations into both curriculum content and design practice (Yu et al., 2025). This includes developing targeted AI ethics training for educators and using real-world cases to examine issues like academic

integrity, algorithmic fairness, and risks of overreliance on generative tools (Marín et al., 2025). Facilitating dialogue and scenario-based learning can also support learners in engaging with ethical dilemmas and making informed decisions (Al-Maaitah et al., 2025).

Limitations

This research has several limitations, so readers should exercise caution. First, although we collected the data over two years, the small number of participants in this study reflects the small class size at the private university in the United States where the study was conducted. Future researchers may consider recruiting a larger number of ID students for this type of study. Second, time constraints precluded interviewing students; doing so may have provided richer contexts and insights from the ID students' perspectives. Last, readers may need to exercise caution when interpreting the results because we collected data during fall semesters in 2024 and 2025. Since then, AI technologies have rapidly evolved, and more people have adopted AI tools in their daily lives. Perhaps more ID students use AI tools now than when we collected the survey data; thus, readers may consider the data to represent the relatively early stages of the AI adoption era.

Declarations

Conflicts of Interest Statement

The authors have no competing interests to declare that are relevant to the content of this article.

Data Availability Statements

The datasets generated during and/or analyzed during the current study are not publicly available as it was not permitted by the IRB.

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Graduate Students at the Frontier of GenAI: Emerging Trends from a Southwest Borderland University

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Abstract

The rapid emergence of generative AI (GenAI) is reshaping higher education, offering both opportunities and challenges. In this context, graduate students are a critical population for examining adoption as they tend to experience both advanced academic work and professional preparation. This study explored graduate students' awareness, uses, perceptions, and future intentions regarding GenAI within the context of taking one or more educational technology courses at a southwest borderland university. A qualitative descriptive, cross-sectional design was employed. Data were collected via an online survey (N = 24) including multiple choice, Likert-scale, and open-ended items. Connectivism served as the primary theoretical perspective, with the Concerns-Based Adoption Model (CBAM) Stages of Concern providing a complementary framework for interpreting adoption patterns. Findings indicated that students moved from limited prior exposure to more deliberate integration of GenAI. Three key thematic trends emerged: (1) promise, productivity, and partnership, where GenAI was framed as a collaborative partnership that augments rather than replaces human agency; (2) boundaries and ethics, including strong concerns about academic integrity, accuracy, equity, and over-reliance; and (3) navigating uncertainty, marked by inconsistent institutional policies and discipline-specific variation. Overall, graduate students are navigating GenAI adoption with enthusiasm tempered by boundary consciousness. They viewed GenAI literacy as increasingly essential for academic and career competitiveness yet stressed the importance of policies and practices that emphasize appropriate augmentation, ethics, and equity in higher education.

Keywords: Generative Artificial Intelligence (GenAI); higher education; graduate students; connectivism; Concerns-Based Adoption Model (CBAM); AI literacy

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Introduction

As of 2025, only three years have passed since the explosive emergence of generative artificial intelligence (GenAI) technologies, which are already reshaping the landscape of higher education and influencing teaching and teacher education, research, and professional practices across disciplines. Its rapid adoption presents both generative affordances alongside complex challenges, particularly for graduate students who are at the intersection of advanced academic study and career preparation (Chan & Tsai., 2023; Barros et al., 2023). As large language models such as ChatGPT, Claude, Gemini, and CoPilot have gained widespread accessibility, their integration into academic workflows has become increasingly prevalent among student populations, particularly at the graduate level where research and analytical tasks predominate (Kasneji et al., 2023; Saúde et al., 2024). This technological disruption has prompted pressing questions about trends in students' use of GenAI focused on academic integrity, originality and creativity, bias, pedagogical effectiveness, and the evolving nature of scholarly work in the digital age.

At a southwest borderland university situated in the New Mexico/Texas/Mexico border region, where unique transnational cultural, linguistic, and socioeconomic factors shape student experiences, examining trends in the use of GenAI provides critical insights into how this technology is reshaping learning and scholarship in diverse academic settings. Graduate students, positioned at the intersection of advanced coursework and independent research, represent a particularly significant demography for examining GenAI adoption patterns. Graduate students regularly engage in research and complex data analytical tasks and thus stand to benefit from AI-assisted data analysis workflows (Drosos et al., 2024). However, the borderland context adds unique dimensions to this technological adoption, as students in these regions often navigate multilingual academic environments, diverse cultural backgrounds, and varying levels of technological access and literacy.

As we developed this study, a key component included identifying trends in how graduate students use emerging and advanced technology tools, particularly in this case, GenAI, in their academic & professional pursuits. As educators in higher education, we focus on examining the role of technology in supporting contextualized knowledge development through active interaction and engagement. In a previous study, two of the authors documented how they navigated the integration of social media and emerging AI tools such as ChatGPT in their online graduate courses at a southwest borderland university (Parra & Chatterjee, 2024). A key observation from that work was the rapid adoption and experimental use of GenAI, especially among graduate students. This was particularly evident when two separate teams in one fall 2023 class about designing synchronous instruction, independently chose to focus their webinar presentation projects on AI in education, indicating not only strong engagement with AI tools but also interest in their purposeful applications.

Our collaborative exploration of AI mirrored our emphasis on structured engagement and addressing concerns about academic integrity, for which we developed a class guide titled "AI Values and Norms," which emphasized transparency and ethical use by students. By prioritizing human connection and sociocultural responsiveness in our own teaching practice, we created a foundation from which this study emerged, examining how GenAI is experienced in higher

education and to highlight the critical voices and perspectives of our graduate students. Thus, the purpose of this study was to explore graduate students' awareness, uses, perceptions, and future intentions regarding GenAI within the context of taking one or more educational technology courses at a southwest borderland university.

Review of Related Literature

The integration of generative AI in higher education has reached a threshold with studies revealing rapid and widespread adoption across diverse academic contexts since the launch of ChatGPT 3.5 in late 2022 (Intorsureanu et al., 2025). Sullivan et al. (2023) found that approximately 43% of college students had used ChatGPT for academic purposes within six months of its public release, while Qu et al. (2024) reported discipline-specific variation, with STEM and humanities students showing different preferences for AI assistance. Freeman (2025) similarly documented undergraduate AI usage surging from 66% to 92% between 2024 and 2025, with GenAI use for assessment increasing from 53% to 88%. Students primarily used GenAI for idea generation, explanation, and article summarization, while 18% directly incorporated AI-generated text into their work.

Recent studies have shown similar patterns of GenAI related complexity, particularly among graduate teaching assistants who navigate dual-role challenges as both students and instructors (Zhang, 2025). This dual positioning creates ethical and pedagogical tensions as they must negotiate personal use with instructional policy, expectations around academic integrity, and evolving institutional guidelines. These complexities parallel broader trends in recent global research. A survey on students and lecturers in higher education institutions across 76 countries reveals high awareness and recognition of GenAI tools, with ChatGPT being the most recognized due to its accessibility and versatility (Yusuf et al., 2024). Institutional surveys show adoption rates are highest among graduate students (66%) compared to undergraduates (56%) and faculty (58%) (Baytas & Ruediger, 2024). Compared to undergraduate students and faculty, graduate students demonstrated more complex usage patterns, particularly in research processes such as literature reviews, statistical data analysis, hypothesis generation, code generation, academic writing and manuscript preparation, reflecting more strategic application of AI capabilities for academic purposes (Yusuf et al., 2024). The primary reasons students cite for use of AI are to save time (51%) and improve the quality of their work (50%), while primary concerns are plagiarism (53%) and getting false results (51%) that discourage usage (Freeman, 2025).

Research on learning outcomes indicates that higher levels of learning occur when students use GenAI to construct knowledge through a mastery approach (Pallant et al., 2025). Competence studies similarly indicate that individual AI competency levels significantly impact how different GenAI tools are evaluated and used for learning and assessment purposes (Heil et al., 2025). Further research shows that graduate students and researchers often view GenAI through three distinct lenses, as a “work horse” for productivity, as a “language assistant only” for editing tasks, or as a “research accelerator” for comprehensive research enhancement (Andersen et al., 2025). Within research contexts, GenAI literacy for graduate students includes developing prompt engineering skills as a key digital competency, with frameworks emerging to guide effective and responsible use in academic research (Francis et al., 2025).

The rapid acceleration of GenAI use has also challenged traditional assessment practices. An analysis of the top 50 U.S. universities found that 94% have developed faculty guidelines emphasizing clear frameworks for GenAI use and generally hold positive attitudes toward AI integration (An et al., 2025). Yet only 29% of students agree that their institutions encourage AI use compared to 40% who disagree, highlighting a persistent policy gap (Freeman, 2025). Universities face concerns about job displacement, particularly for graduate students who rely on teaching assistant roles for financial stability and professional development, as these roles involve grading and administrative tasks that are increasingly at risk of AI automation (Capano et al., 2025). Consequently, the dual-edged nature of GenAI integration underscores the need for frameworks that complement rather than replace human proficiencies, with institutions balancing innovation opportunities against concerns about academic integrity, authenticity, and the development of essential cognitive skills (Capano et al., 2025).

Overall, these studies illustrate widespread adoption, growing sophistication of use, and a complex landscape of ethical, instructional, and institutional tensions. However, significant gaps remain in our understanding of how awareness, usage and perspectives influence GenAI adoption and usage patterns among graduate student populations specifically. Further, student voice is limited yet critical in the ongoing GenAI discussions (McGrath et al., 2025; Bearman et al., 2025).

Theoretical Framework

This study draws upon two frameworks: Connectivism (Siemens, 2005; Downes, 2008; Goldie, 2016) and the Concerns-Based Adoption Model (CBAM), with CBAM applied specifically through the Stages of Concern (Hall & Hord, 2015). Connectivism was identified early as central to the understanding of GenAI as a learning phenomenon, while adoption models informed the survey design through constructs such as “awareness,” as noted in Rogers’ Diffusion of Innovations (2003) and in early documentation of CBAM (Hord & Loucks, 1980). Rogers’ model and the CBAM Levels of Use (Hall & Hord, 2015) were initially considered for an additional framework; however, these models felt more linear, assuming stable, routine implementation patterns that did not align with the incredibly rapid, emergent and uneven nature of GenAI use in higher education. In contrast, CBAM’s Stages of Concern offered a more appropriate lens for this study because it captures the emotional, cognitive, and informational sense-making that individuals experience when encountering a rapidly evolving innovation.

Connectivism (Siemens, 2005; Downes, 2008; Goldie, 2016), serves as the study’s primary theoretical foundation, emphasizing learning occurs across dynamic networks of people, resources, and non-human entities such as digital technologies. Within this view, these entities function as “nodes” in a knowledge network. Knowledge is viewed as distributed, and the learners gain understanding by accessing and engaging with diverse nodes across networks. Further, learning is understood as a continual process, since knowledge evolves rapidly and the ability to discern patterns across networks is central to meaning making. GenAI, in this context, acts as an additional node in graduate students’ academic and professional networks. It expands the range of connections available to learners, enabling them to draw on machine-generated insights alongside human and material resources. Connectivism therefore provides a lens for

understanding how students situate GenAI within broader ecologies of knowledge and how they adapt their learning practices in dynamic, technology-mediated environments.

While Connectivism serves as the primary theoretical foundation, the Concerns-Based Adoption Model (CBAM) (Hall & Hord, 2015; Hord, Rutherford, Huling, & Hall, 2014) emerged as a complementary lens for interpreting how participants, in the roles of both students and practitioners, made sense of, used, and began to adopt GenAI tools. CBAM includes three principal dimensions: (1) Stages of Concern, (2) Levels of Use, and (3) Innovation Configurations. The Stages of Concern were most relevant for this study as they emphasize that adoption-related concerns are often non-linear, overlapping, and context dependent (Hall & Hord, 2015; Hord, Rutherford, Huling, & Hall, 2014). These seven stages—unconcerned (originally termed “awareness”), informational, personal, management, consequence, collaboration, and refocusing—provided a practical interpretive vocabulary to discuss participants’ responses in this study. These stages provided some of the language for describing and interpreting the graduate student adoption patterns that included uncertainty, exploration, enthusiasm, as well as hesitation, a well-suited framework for discussing early-stage GenAI integration. Of note, the shift from “awareness” to “unconcerned” in the recent iteration of the model raises an interesting tension for educators. The term “awareness” denotes an implicit pedagogical imperative that positions educators as active facilitators of engagement rather than merely respondents to a lack of concern. This is a distinction that warrants further future exploration, particularly in contexts of early-stage technology adoption.

Methods

A qualitative descriptive, cross-sectional design was used for this study, with the goal of capturing a “snapshot” of graduate students’ current awareness and use of GenAI, as well as their perceptions, attitudes, and future outlook. This design was well-suited to exploring experiences and perspectives rather than examining changes over time or the effects of a formal intervention. The following four key research questions were addressed with this study:

RQ1. What are the current trends in graduate students’ awareness, experiences, and use of GenAI in academic and professional contexts?

RQ2. How do graduate students perceive the benefits, challenges, and ethical boundaries of integrating GenAI into their learning and teaching practices?

RQ3. What institutional policies, practices, and guidance shape graduate students’ use of GenAI?

RQ4. What future intentions and outlooks do graduate students hold for the role of GenAI in their academic, professional, and personal lives?

Participants and Context

Participants were drawn from 69 graduate students who, between summer 2024 and fall 2025, completed one or more courses in online educational technology at a southwest borderland university that were taught by one of the study’s co-authors. This co-author is also the coordinator for the educational technology program at this university. The program offers two graduate-level options, a master’s program consisting of 10 courses and a graduate certificate

program consisting of four courses. The student body includes preservice and in-service K–12 teachers, community college and university faculty, doctoral students among others. Many are practicing educators balancing graduate study with professional responsibilities. The program reflects the university's diverse borderland context, with representation from Hispanic/Latinx and multilingual populations.

The participants of this study include those in one of the online educational technology programs or those taking one course as an elective. Course topics included instructional design for blended and online instruction, educational technology integration (including GenAI), technological, pedagogical and content knowledge (TPACK), and culturally responsive learning environments fostering community (Chatterjee & Parra, 2021). All courses were delivered fully online, primarily asynchronously with opportunities for synchronous engagement through class meetings, team meetings, and one-on-one instructor and student conferences.

Students' exposure to GenAI was partly shaped by the program curriculum itself. For example, instructors had begun integrating AI-related tools and discussions into coursework to model potential applications of these technologies in teaching and learning. While this was not a formal intervention designed by the research team, it formed part of the natural learning environment influencing participants' awareness and use of GenAI.

Data Collection

Data were collected using an online survey (see Appendix A) titled, *Research Questionnaire: Perceptions and Usage of Generative AI in Academia*. The survey consisted of five domains: Background and Demographics; Prior Exposure and Program Context; Awareness and Usage of Generative AI; Perceptions and Attitudes; and Future Outlook. Items were a mix of multiple-choice, Likert-scale ratings, and open-ended text boxes enabling both descriptive trend data and narrative elaboration. The members of the research team met in Zoom several times to discuss and collaboratively develop the survey. The survey instrument (see Appendix A) was designed to capture graduate students' experiences with GenAI across the noted five domains. These domains map onto the four overarching research questions that guided the study (see Appendix B).

Students were recruited via an email distribution list provided by the co-author who was also program coordinator and instructor for the educational technology courses referred to in this study. One researcher who was not the instructor created and sent the recruitment emails. Participation was voluntary, informed consent was embedded in the invitation and survey introduction, and no incentives were provided. The survey was sent at the beginning of summer 2025 and remained open through the first two weeks of class at the southwest borderland university, with a reminder email sent by the other researcher, also not the instructor, at the beginning of the fall 2025 semester. The survey remained open for an extended period, with two additional responses received after initial analysis began. The final dataset included 24 responses.

Data Analysis and Trustworthiness

Given that one researcher was also the instructor of record for the participants of this study who were graduate students at the university and who represent a protected class, this co-author did not have access to the raw survey data and identifiable information until after the class concluded and grades were posted. This procedural separation ensured that instructional roles did not intersect with data handling or early analysis. Analytic rigor was enhanced through multiple strategies, including analyst triangulation, peer debriefing via Zoom meetings, and the maintenance of an audit trail documenting analytic memos and coding decisions.

Descriptive statistics (frequencies and percentages) were calculated for closed-ended items. Open-ended responses were examined through a multi-stage qualitative content analysis conducted by the four authors. First, two researchers independently reviewed the data and met to discuss preliminary impressions and recurring patterns and themes. One of these researchers then drafted paragraph-level summaries for each survey question to synthesize emerging patterns. Next, the instructor/coauthor reviewed these summaries, to clarify wording, collapse overlapping categories, and strengthen the organizational coherence of the analysis. A fourth researcher subsequently examined the analytic outcomes to confirm consistency and provide an additional interpretive check. Finally, all authors reviewed the manuscript holistically to ensure shared understanding and consensus regarding the analytic interpretations. Due to the small sample size of this study, the research team did not require the use of large-scale qualitative data analysis software such as Qualtrix or NVivo. Instead, qualitative data analysis in this work was assisted by OpenAI's GPT-4.

Results

The results of this study align with emerging trends in the use of GenAI. Trends signal both measurable shifts and evolving priorities directly impacting the field. Similarly, the results of this study provide insight into patterns and shifts in graduate students' engagement with GenAI. These results contribute to broader conversations about GenAI use and implementation in academia. The study design enabled the collection of both descriptive data on usage patterns and rich qualitative reflections on participants' experiences, concerns, and perspectives of GenAI in education.

The results of the administered survey are organized around five domains (1) demographic and professional background; (2) prior exposure to and program context of GenAI; (3) awareness and usage of GenAI tools; (4) perceptions of and attitudes (e.g., usefulness, productivity, academic integrity); and (5) future outlook in regards to GenAI (e.g., benefits, challenges, contextual trends, institutional support). Following is a description of our results framed by the five domains listed above.

Domain 1: Demographic and Professional Background

Current Roles

Of the 69 graduate students who were invited to participate, 24 took the survey, representing a diverse cross-section of the academic community. Community college faculty members (n = 10) comprised the largest group followed by K-12/Inservice educators (n = 6).

Other professional roles represented included university faculty members ($n = 2$), community college staff ($n = 1$), and program specialists ($n = 1$). Given the small sample size and limited number of demographic categories, participant roles are reported narratively rather than in a table.

Many of the participants held dual roles as both students and educators. This dual positioning, as learners engaging with GenAI in their coursework while simultaneously considering its pedagogical applications, provides a unique vantage point for understanding adoption patterns in higher education.

As noted by the researcher who also serves as instructor and program coordinator, the high proportion of community college faculty in the sample reflects the presence of a funded cohort from a local community college. This cohort's participation underscores how institutional partnerships can influence the composition of the student body in program-level research. Notably, edtech courses are also available to students across campus, including doctoral students, which further contributes to the diversity of professional and academic backgrounds represented in the study sample.

Domain 2: Prior Exposure and Program Context

Prior to Taking Courses in Educational Technology

The survey responses for the question about participants' experience prior to taking educational technology courses indicated that most graduate students entered the courses with limited to minimal prior exposure. Most respondents described having little to no prior experience, noting "no experience," "none to very little," or only casual familiarity with AI systems embedded in social media platforms like Google or Facebook. This suggests that for many students, the structured exploration of AI-related topics began within the context of their edtech coursework.

There were several outliers who provided a notable contrast to this overall trend. One respondent mentioned having five years of military experience, which may have provided indirect exposure to AI-driven technologies, though the context was not detailed. Another identified as a self-researcher/enthusiast, signaling a proactive personal interest in AI that likely predated formal instruction. A third participant reported experimenting with AI-based lessons for upper elementary and middle school students, suggesting early adoption of GenAI into teaching practice.

Beyond these outliers, the overall data indicate that students entered the program with low levels of GenAI familiarity. The presence of students who had basic accounts with tools like ChatGPT, but only used them for simple queries, highlights an important distinction between awareness of AI tools and meaningful engagement with them. Many students knew of AI tools but had not yet leveraged them for academic or professional tasks. This gap reflects a broader trend in higher education in which public awareness and casual use have grown rapidly but deep and purposeful integration into academic or professional practice has lagged.

Exposure and Experiences with AI-Related Activities in EdTech Courses

Responses to the question about AI-related activities reflected a broad range of GenAI engagements. In contrast to the baseline data responses about prior use, where most students reported minimal or limited prior exposure, these responses highlighted structured activities, guided reflection, and critical discussions as central features of their exposure and experiences in EdTech courses. Increased efficiency and productivity were impacted, whereby several students described assignments that introduced AI as a support tool for academic tasks such as using virtual assistants, generating outlines, or helping locate sources. These activities were valued for saving time and improving organization, with students noting “how useful AI is” and that they “appreciate how time efficient it is.”

Creative introductory activities were another type of activity discussed. Examples included creating superhero characters, designing AI self-portraits, or producing digital artwork. These activities allowed students to experiment with generative tools in playful and imaginative ways while also exposing some of the limitations of AI including inaccuracies in representing cultural identity or physical features. These experiences demonstrate how AI can be positioned as both a creative partner and a learning object, fostering student awareness of its strengths and weaknesses. For example, avatar creation emerged as a particularly memorable activity, with multiple students recalling this exercise. These avatar-based activities served dual purposes: introducing students to GenAI’s creative capabilities while simultaneously revealing its limitations in accurately representing diverse cultural identities and physical features, a critical learning moment about AI bias.

A third recurring type of experience focused on the ethical, safe, and critical engagement of AI. Students recalled discussions and assignments that addressed topics like bias, academic integrity, hallucinations, copyright, and proper citation of AI-generated content. One student cited the guideline to “trust but verify”, reflecting encouragement to use AI critically rather than uncritically accepting its outputs. Others emphasized that AI should be positioned as an assistant, not the leader, which demonstrates awareness of maintaining human agency in academic and professional work.

Iterative practice and reflections were another type of engagement for respondents. They remembered AI-related activities that included exploratory tasks, such as technology evaluations or research-related exercises, and even tailored examples for math students. The reflective component, where students transparently disclosed their processes and critically examined their AI use (e.g., including an AI statement in coursework), indicated that AI was framed not only as a tool for efficiency but also as a subject of inquiry, aligned with professional and academic responsibility.

Finally, some participants commented on broader societal implications. One student noted learning to use AI as a conversation partner and to “ensure that I was stating things in a culturally responsive way and did not hold any unknown biases.” Another student described AI as “complicated” and difficult for society to fully grasp, observing how the media tends to amplify fears while underplaying AI’s increasing integration into daily life. Such comments suggest that students’ critical consciousness was being shaped not only by the tool-based

activities but also by the course discussions that were extended to include cultural narratives and public discourse around AI.

Overall, these responses suggest that the integrations of AI-related activities into edtech courses moved students from minimal prior exposure to active and reflective engagement within EdTech courses. Through a combination of productivity-focused tasks, creative assignments, and structured discussions regarding culture and ethics, students reported developing a nuanced understanding of AI's potential and its limitations.

The results of the administered survey are organized around five domains (1) demographic and professional background; (2) prior exposure to and program context of GenAI; (3) awareness and usage of GenAI tools; (4) perceptions of and attitudes (e.g. usefulness, productivity, academic integrity); and (5) future outlook in regards to GenAI (e.g., benefits, challenges, contextual trends, institutional support).

Domain 3: Awareness and Usage of GenAI

Familiarity with GenAI Tools

Responses for students' familiarity with GenAI tools reflected a tiered adoption pattern. Students reported near-universal reliance on general-purpose GenAI tools, a moderate engagement in creative and education-focused tools, and limited use of specialized/niche or technical models. To better understand this tiered adoption, we report which applications students engaged with most frequently and the specific usage of the applications.

ChatGPT (100%), Gemini (75%), CoPilot (62.5%), and Claude (50%) were the most widely used general-purpose AI applications, supporting writing, summarization, coding, and productivity tasks. Participants reported using the following applications for visual content generation and design tasks: Canva Magic Studio (50%) and MidJourney (16.7%). Magic School AI (50%) emerged as a prominent education-focused tool supporting lesson planning, content creation, and accessing teaching resources. Tools like Deepseek (20.8%), Meta Llama (12.5%), Qwen (4.2%), Cohere (0%), and Falcon (0%) reflected lower levels of awareness or usage often associated with more technical or research-specific use cases.

Beyond the listed survey options, students reported using additional tools. For example, a category of tools that surfaced includes existing software that has integrated AI features such as Adobe Acrobat with integrated GenAI art functions. Others, such as Perplexity, Boodlebox, and NotebookLM/Google Notebook, highlight interest in integrating platforms that support knowledge organization and Application Programming Interfaces (API) based access to multiple AI systems. ChatPDF was a tool that further illustrated the value of AI in academic contexts by enabling interactive engagement with texts. These responses illustrate an exploratory interest in extending AI use across diverse academic, professional, and creative contexts.

GenAI Tools Students Are Most Familiar with and How They Use Them

ChatGPT was by far the most widely referenced tool, appearing in nearly every response. Students reported using it for brainstorming, writing support, research, proofreading, lesson planning, and curriculum development. Other frequently noted tools included CoPilot (widely available through institutional access), Gemini, and Claude, each used for more specific purposes. CoPilot was valued for outlining, revising writing, and sourcing materials, while Gemini was often used as a secondary option, offering alternative perspectives or supporting specific course-related tasks, and Claude was used for coding.

Education-focused tools like Magic School AI and ChatPDF were recognized as valuable for curriculum design, resource development, and document analysis, demonstrating their relevance to graduate-level coursework and teaching preparation. Some respondents also described experimenting with Perplexity (AI powered search tool), Craiyon (image generation tool), NotebookLM/Google Notebook (research/knowledge management tool), and Boodlebox (AI platform designed specifically for education), highlighting curiosity beyond mainstream tools. Overall, these responses indicate that students are moving from basic awareness to purpose-driven application, with GenAI tools supporting their own academic and professional work as well as their teaching practices, professional development, and student-centered instruction.

Frequency of Use

Patterns of frequency varied across the 24 respondents. About one-third (33.3%, n=8) reported daily use, integrating AI regularly into academic and professional routines. The largest group (37.5%, n=9) used AI weekly, while 25% (n=6) reported occasional use. While only one respondent (4.2%) reported never using these tools. These results indicate that nearly 70% engage at least weekly with AI, which underscores a strong overall presence of GenAI in the academic, personal, and professional lives of graduate students.

Purposes for Which Students Used GenAI Tools

Students described a range of purposes for which they used GenAI. The most common was brainstorming or idea generation (95.8%), reflecting AI's role as a thought partner. Writing assistance was also widespread (79.2%), including drafting, editing, and revising academic assignments. More than half of the respondents reported using AI for graphic or media creation (66.7%), and more than half (54.2%) demonstrated that they were beginning to integrate AI into teaching practices, lesson planning, rubric creation, and educational presentations. Activities gaining traction included coding or technical tasks (20.8%) and research design or analysis (45.8%). Fewer responses were recorded for grading or feedback (12.5%), while one participant reported no usage at all. Several responses extended to supporting personal uses such as gardening, cooking with macros-based recipes, and designing fitness routines. Overall, the data reveal that students primarily adopt AI for idea generation, writing, and creative work, with limited integration into technical and evaluative functions. These results may serve as early indicators of trends in future use of GenAI.

Intentions for Future Use

Nearly all respondents indicated plans to continue using GenAI in the future, though in varied ways. Common intentions included using it for efficiency and productivity, particularly in drafting, lesson planning, content creation, and resource development. Several noted that AI helps reduce time spent on routine academic tasks, freeing them to focus on higher-order thinking. Several participants anticipated expanding into research design, data analysis, and media creation, while others emphasized its value for refining tone, clarity, and accuracy, in particular for multilingual learners and emergent English language speakers.

Respondents also acknowledged the importance of using GenAI critically, framing it as a support tool rather than a replacement, while noting intentions to critically engage with issues of accuracy, bias, and equity. A few responses highlighted the importance of teaching about AI, signaling a desire to introduce students to responsible practices and integrate AI-focused activities into classrooms. One respondent mentioned personal uses such as vacation planning and business ideation. Overall, intentions suggest sustained and expanded adoption, balanced by an awareness of ethical and pedagogical considerations and mirroring broader trends surrounding the ethics of AI usage

Reflections Prompted by the Survey

The final open prompt in this section elicited deeper reflections on GenAI use. Several participants reported that the survey itself prompted them to think more critically about their daily practices, not only as a support for productivity but also as something that shapes their leadership, teaching, and modeling of responsible use. Responses emphasized a tension, especially in their educational contexts, between fear and opportunity. Some educators worried that AI could replace them, and others reframed it as a tool that enhances learning. Concerns about plagiarism and institutional ethics were frequently raised with a trend towards reverting to paper assignments as a way to avoid misuse.

Some participants expressed curiosity about lesser-known AI tools, calling for more exposure and training. Several participants emphasized the value of AI Use Statements, detailed instruction for AI use, and clear citation practices as strategies for guiding ethical integration. Overall, these reflections reveal both hope and hesitation, underscoring the need for professional development that addresses concerns, emphasizes ethics, and empowers educators to confidently integrate AI.

Domain 4: Perceptions and Attitudes Toward GenAI

Helpfulness in Learning and Teaching Practice

Survey responses indicated overwhelmingly positive perceptions of GenAI in teaching and learning. None of the respondents rated these tools as “not helpful,” while only one respondent (4.2%) rated it “slightly helpful.” Almost one third (29.2%) of participants found GenAI “moderately helpful,” while 37.5% rated it as “very helpful,” and one third (33.3%) rated it as “extremely helpful.” This distribution shows that students largely view GenAI as more than a marginal aid, positioning it instead as a valuable tool for enhancing efficiency, creativity, and pedagogical support.

Agreement with Statements on Productivity, Integrity, and Institutional Support

Participants were provided with a series of statements to select if they agreed with the statement. Like recent trends in AI, participants reported agreement with statements highlighting GenAI’s practical benefit. A large majority (79.2%) agreed these tools improve productivity and support personalized learning. Half (50%) expressed confidence in their ability to use GenAI effectively. At the same time, concerns were evident with 83.3% of respondents worried about issues of academic integrity and half (50%) agreed that GenAI limits original thinking or creativity, indicating that while students embrace the utility of GenAI, they remain cautious about its implications.

The data also revealed a potentially significant issue with institutional support. Only 25% of participants agreed that their institution has provided adequate guidance on AI use. These results suggest that the participants are embracing productivity and learning benefits but also navigating ethical challenges and institutional ambiguity largely on their own.

Domain 5: Future Outlook in Regard to GenAI

Potential Benefits

Participants identified three primary areas of benefit from integrating GenAI into higher education: (1) productivity and efficiency, (2) accessibility and personalization, and (3) pedagogical innovation. Productivity and efficiency were the most frequently cited advantages with respondents emphasizing timesaving, streamlined research processes, and increased output potential. Several noted that GenAI provided quicker access to academic resources and enabled more efficient writing processes, helping to address bottlenecks in graduate-level work.

Accessibility and personalization were highlighted with students describing GenAI as “your own tutor at any time,” and in alignment with Universal Design for Learning (UDL) principles. They noted that such 24/7 availability could particularly benefit diverse populations and students who require additional scaffolding for complex tasks. One participant explicitly connected GenAI to UDL for Learning principles, noting, “we will be able to create assignments that support a wider range of students.” This connection between GenAI and established pedagogical frameworks suggests that adoption is not occurring in isolation but is integrated with existing educational best practices.

Finally, respondents pointed to pedagogical innovation, citing GenAI's capacity to spark new ideas, offer alternative perspectives, and enable or expand creative applications such as media production. Collectively, these responses suggest that students see GenAI as a tool that can complement and enhance, rather than replace, human creativity and instructional practice.

Challenges and Concerns

While participants expressed enthusiasm for the potential benefits of GenAI, they also voiced five main categories of concern. The most frequently cited challenge related to academic integrity, with multiple respondents explicitly mentioning cheating, plagiarism, and integrity violations. Several participants expressed fear that GenAI use could result in students doing only the "minimum work" without fully understanding, engaging in, or learning from their assignments.

Another area of concern focused on over-reliance and skill atrophy, as respondents worried that students might become dependent on AI tools rather than developing critical thinking and creative problem-solving abilities. Concerns about information accuracy and bias were also common, with respondents noting hallucinations, misinformation, and the ongoing need for fact-checking. Students recognized that GenAI outputs require verification and expressed worry about accepting AI-generated content without critical evaluation.

Equity and access disparities emerged as another concern, with one respondent noting how socioeconomic factors could create educational gaps between students who can access premium AI tools and training versus those who cannot. Finally, respondents mentioned faculty adaptation challenges, noting that some educators were "not willing to change their knowledge testing" methods to accommodate new technological realities.

Overall, these categories of concern suggest that the participants understood that successful GenAI integration requires institutional and pedagogical transformation beyond simple tool adoption.

Observed Trends in the Field

When asked about trends in their environment and fields, respondents described disciplinary variation in GenAI adoption, with distinct patterns emerging across different contexts. In higher education administration, GenAI was noted as being strategically integrated for "drafting reports, preparing presentations, and brainstorming ideas," suggesting professional applications with accompanying ethical discussions about "trust" and appropriate usage.

In creative fields, they reported both resistance and adaptation. One respondent, self-identified as an art educator, commented that "the art that AI produces is terrible" while also acknowledging its utility for graphic design and spatial planning. This reflects an understanding of AI's creative limitations while recognizing its practical value, reinforcing the idea of AI as a complement rather than a replacement of human creativity.

In healthcare and technical fields, respondents described cautious experimentation. Dental radiography applications, for example, were acknowledged as advancing but “not super reliable...yet,” pointing to professional use cases that require further validation before broader adoption. In K-12 education, concerns about “plagiarism” and reliance on “AI checkers,” were prominent alongside positive applications including AI-generated podcasts for “lesson starters” and goal-setting assistance for students.

Several respondents indicated ubiquitous integration across software platforms, with one noting AI embedded in “most software coming out,” including enterprise systems like Oracle. This signals infrastructural adoption beyond individual choice. Across contexts, however, privacy concerns remained paramount. One respondent observed that institutions were “slowly starting to open up to AI but the concern about privacy is always brought up.” Another noted that AI had begun taking over “students and our office hours” suggesting workflow disruption that required adaptation.

Overall, respondents described GenAI integration as expanding and likely inevitable across disciplines, but still in a transitional phase. They emphasized that while applications are emerging in field-specific ways, concerns about ethics, privacy, and quality continue to demand careful management. Taken together, these findings indicate that participants are increasingly engaging with GenAI in informed and purposeful ways. However, this engagement is occurring in the context of inconsistent or unclear institutional guidance, which becomes more apparent when examining institutional policies and practices.

Institutional Policies and Practices

The data revealed a concerning pattern of policy awareness, with multiple respondents explicitly stating they were ‘unaware’ or ‘not sure’ about institutional guidelines. This suggests not merely inadequate policies but also a communication failure, where existing guidelines may not be reaching their intended audience effectively. For example, the data revealed a significant gap in institutional support. Less than one-fourth (22.2%) of participants agreed that their institution has provided adequate guidance on AI use. Taken together, these results suggest that the participants are simultaneously confident and concerned. They are embracing productivity and learning benefits but navigating ethical integrity challenges and institutional ambiguity largely on their own.

Participants described an inconsistent institutional approach to GenAI policies. Most noted that guidance was provided at the syllabus-level, with individual instructors making independent decisions about how AI could be used in their courses. A common approach involved three possible syllabus statements, ranging from broad permission to conditional use to no use of GenAI. However, these statements tended to emphasize citation and disclosure requirements rather than offering substantive guidance on appropriate or effective use. This created what one respondent referred to as a “gray area,” where expectations varied widely from class to class.

Awareness gaps were also evident. Several respondents noted that they were unfamiliar with institutional policies or were not “up to date” on current guidelines, suggesting that even when formal policies exist, they were not well communicated. The instructor-dependent

approach means students must navigate different AI expectations in each course, potentially creating confusion about academic standards. Most concerning is the apparent absence of comprehensive institutional frameworks, leaving both faculty and students to independently interpret appropriate GenAI usage without clear, unified guidance from administration.

Overall, participants experienced policies and practices as fragmented and inconsistent. While some courses provided comprehensive guidance and resources, others offered minimal syllabus statements, leaving students and educators to navigate without clear institutional frameworks. Beyond institutional policies and practices, participants also reflected on their intentions for future use of GenAI and the personal trends shaping how these tools might be integrated across academic, professional, and everyday contexts.

Intentions for Future Use and Personal Trends

When describing intentions for future use and future trends for use of GenAI, participants expressed a spectrum of intentions ranging from enthusiastic adoption to deliberate avoidance. Most respondents anticipated continued or expanded use, while at least one expressed a desire to avoid AI tools entirely. For example, one respondent explained they were moving “toward using AI as a partner in creative and professional work rather than just as a quick productivity tool.” Within this spectrum, an overarching trend was the view of GenAI as a collaborative partnership, an evolution from seeing it as a simple productivity tool to recognizing it as a partner in creative and professional work.

Respondents described task-specific adoption patterns that reflected purposeful, strategic use. This included research assistance, writing support, data analysis, and administrative tasks like activity tracking and planning. Several noted using AI for “tedious tasks” and “busy work,” suggesting strategic deployment for efficiency rather than for core learning activities. Language refinement and communication enhancement appeared frequently, with multiple respondents using GenAI to improve “wording,” “professional language,” and “communications.” This suggests GenAI serves as a writing assistant, helping students achieve professional-grade expression. One respondent referred to using AI as a “brainstorm tool when I need the extra push” highlighting its role in conceptualization. Respondents also expressed anticipation of expanding capabilities, especially in multimedia creation, with one noting they expected increased use of “image or video generation as it gets better.”

Respondents highlighted professional and pedagogical applications noting that GenAI was already supporting accreditation documentation, instructional activity development, lesson planning, and career preparation. One respondent described using GenAI for “addressing and documenting professional standards,” illustrating how they leveraged AI for professional tasks requiring precision. Others mentioned applications related to enhancing classroom practice and one noted using it to prepare for a STEM related job.

A pattern of boundary consciousness emerged, with one respondent explicitly stating, “I don’t want AI to speak, think, or take over for me. I see it as a supportive tool, not as a replacement.” At the same time, professional integration was seen as increasingly necessary with another respondent noting that “if you’re not using AI, you’re slowly falling behind.” These

perspectives suggest that GenAI literacy is becoming perceived as essential for career competitiveness and productivity, even as students remain committed to maintaining human agency.

Finally, participants described personal and daily-life applications, including routine use of voice assistants for information needs, budgeting and vacation planning. The ubiquity of GenAI was evident with one respondent observing that it is now “available in almost everything online,” which suggests a trend in adoption being partially driven by built-in integration, rather than deliberate choice. Collectively, these accounts indicate that students expect to use GenAI across the multiple life domains of work, school, and personal contexts, and that adoption often follows a progression from simple queries in daily life to complex academic and professional collaborations.

Discussion

This study explored graduate students’ awareness, uses, perceptions, and future intentions regarding GenAI in the context of taking one or more educational technology courses at a southwest borderland university. The findings revealed enthusiasm for GenAI use across their life domains, tempered by significant concerns. Students recognized GenAI as valuable for productivity, creativity, and professional preparation, yet consistently emphasized boundaries, ethical concerns, and the need for institutional guidance. Three key thematic trends emerged from the results of this study: (1) promise, productivity, and partnership; (2) boundaries and ethics; and (3) navigating uncertainty. To frame these trends, we draw upon the four initial research questions alongside our complementary frameworks of Connectivism (Siemens, 2005; Downes, 2008; Goldie, 2016) and the Concerns-Based Adoption Model’s (CBAM) Seven Stages of Concern (Hall & Hord, 2015). For this study, Connectivism highlights the networked dimensions of how students are adopting GenAI as a node within their evolving knowledge ecosystems, while the CBAM Stages of Concern captures the affective and developmental dimensions of how students feel about and make meaning of that adoption.

Promise, Productivity, and Partnership

Students who began with limited prior exposure to GenAI, as noted in the results, have, through their coursework, developed current practices that span a productivity spectrum and are looking ahead to future applications. The findings indicate that graduate students perceived GenAI as part of a promising evolving trajectory from basic productivity tool to collaborative partner. Within this broader trajectory, students in our study described GenAI use ranging from simple tasks (e.g., simple queries, activity tracking) to complex professional applications (e.g., accreditation documentation, lesson planning, and career preparation).

Across this spectrum, students consistently framed GenAI as a collaborative partnership. For example, one respondent explicitly described moving “toward using AI as a partner in creative and professional work rather than just as a productivity tool,” highlighting a shift from instrumental use to partnership-oriented adoption. This notion goes beyond productivity; it represents a fundamental shift in their relationship with GenAI, positioning GenAI not only as a

tool for efficiency but also as a supportive partner in students' professional and academic networks. From a connectivism perspective, this illustrated how learners were expanding their knowledge ecosystems to include GenAI as a non-human node that contributed to problem-solving, brainstorming, and meaning making.

These findings addressed both current practices (RQ1) and forward-looking intentions (RQ4); and they aligned with research describing GenAI as a form of intelligence augmentation rather than a replacement (Jarrahi, 2018) as well with recent work showing that students strategically deployed AI for simpler productivity tasks to free their time for higher order thinking (Yilmaz & Yilmaz, 2023; Gerlich, 2025; Lee et al., 2025). Students looked forward to anticipated improvements with GenAI, as expected for example, in multimedia creation. Further, students perceived GenAI literacy as increasingly necessary for professional competitiveness and as part of an inevitable collective trend of experimentation across disciplines.

Boundaries and Ethics

While the results highlighted students' recognition of GenAI's productivity and learning benefits, they also revealed persistent concerns that tempered this enthusiasm. The second research question (RQ2) asked how graduate students perceived the benefits and challenges of GenAI in academic and teaching contexts. Alongside enthusiasm, students voiced substantial concerns, especially around academic integrity (83.3% of respondents), plagiarism, and skill atrophy. They worried that over-reliance on GenAI, with it "doing the work," could reduce critical thinking and authentic learning experiences. They also identified challenges of accuracy and bias, citing hallucinations and the need for verification. These concerns revealed the emergence of critical AI literacy, where students not only used AI but interrogated its limitations.

The concern about job displacement emerged with particular poignancy among graduate students who serve as teaching assistants. They occupy a dual position as both learners and emerging professionals in the same academic ecosystem where displacement anxieties are rising. As one respondent noted, the fear extends beyond academic integrity to fundamental questions about professional futures and elimination of jobs. This aligns with Capano, He, and McMinn's (2025) findings about graduate students' dual vulnerability as both learners and workers in the academic ecosystem.

One particularly important outcome of this study is the articulation of boundary consciousness: "I don't want AI to speak, think, or take over for me. I see it as a supportive tool, not as a replacement." This emphasis on augmentation rather than substitution echoes existing research (Chan & Tsai, 2023; Dégallier-Rochat et al., 2022) and underscores a key implication of RQ2- that GenAI should augment, not replace, classroom learning and teaching, with educators remaining central to humanizing education.

From a CBAM perspective, these responses reflect overlapping stages of concern: consequence-level concerns in recognizing risks to integrity, equity, and quality and refocusing-level concerns in imagining expanded uses such as multimedia creation. Unlike linear adoption models, our findings begin to show that students inhabit multiple stages simultaneously, negotiating enthusiasm and hesitation in parallel. The continuum between caution and curiosity

suggests that GenAI usage is a negotiation in which students grapple with what it means to think, create, and integrate GenAI in an academic landscape. In this way, CBAM helps illuminate not only how GenAI is adopted but also how to make meaning of its role in shaping identities as learners, researchers, and educators.

Navigating Uncertainty

While the third research question (RQ3) asked what institutional policies, practices, and guidance shape student use of GenAI, the findings also intersect with broader concerns from RQ1, RQ2, and RQ4. Students described uncertainty not only at the institutional level, but also in relation to emerging adoption trends across fields, epistemic reliability, and equitable access to future opportunities.

At the institutional level (RQ3), only 22.2% of students felt their university had provided adequate guidance, leaving them to operate in what one described as a “gray area.” Policies were typically communicated at the syllabus level and varied widely between courses, creating inconsistent experiences. This was particularly concerning given students’ reliance on GenAI for high-stakes tasks such as professional documentation. At the disciplinary level (RQ1), students observed wide variation in how GenAI is approached. An art educator critiqued AI’s creative limitation, a healthcare professional described cautious experimentation with diagnostic applications, and all educators voiced plagiarism concerns. These differences highlight the need for discipline-sensitive approaches rather than one-size-fits-all policies.

Students also grappled with epistemic uncertainty (RQ2), noting hallucinations, bias, and misinformation as ever-present risks. This added a layer of complexity wherein AI was seen as ubiquitous and “available in almost everything online,” its reliability remained contested and uncertain. Finally, equity concerns (RQ4) underscored uncertainty in access. Some respondents worried that socioeconomic disparities could widen as wealthier students accessed premium tools and training while others were left behind, creating a different type of digital divide. These concerns echo anxieties not only about present inequities but also about the trajectory of GenAI adoption in all contexts.

Collectively, these findings suggest that uncertainty is not limited to institutional policy (RQ3) but extends across adoption trends (RQ1), perceived challenges (RQ2), and future outlooks (RQ4). From a connectivism perspective, students are actively negotiating the boundaries of their knowledge networks and selectively integrating GenAI nodes while simultaneously evaluating, critiquing and bounding their use. This selective integration reflects what Siemens (2005) described as the capacity to recognize when to act on current information, a skill that is particularly complex when the nodes themselves are contested, inequitable in access, and epistemically unstable.

From a CBAM Stages of Concern perspective, these overlapping uncertainties reflect management-level concerns about how to use GenAI responsibly and consequence-level concerns about its broader impact on learning, equity and professional futures. Notably, rather than stalling adoption, these concerns appear to be generative, supporting students with the development of personal frameworks for responsible use even in the absence of institutional clarity, suggesting movement through iterative cycles of evaluation that do not map neatly with

the CBAM Seven Stages of Concern. This finding reinforces the value of CBAM's Seven Stages of Concern not as a prescriptive ladder but as a diagnostic lens for understanding the complexity of adoption in rapidly evolving technological contexts.

The findings suggest that these graduate students are not simply passive recipients of technology policy; rather they are active participants in shaping their own GenAI practices with critical intentionality as they navigate institutional, disciplinary, and epistemic uncertainties of an emerging technological landscape.

Conclusions

Taken together, the findings of this study demonstrate that graduate students are navigating GenAI adoption with a balance of promise, productivity, and partnership. They are strategically deploying AI tools for efficiency and professional applications while simultaneously redefining their relationship to the technology through a lens of collaborative partnership. This perspective frames GenAI not only as a tool that augments productivity but as a supportive element across students' networks, tempered by a strong sense of boundary consciousness that emphasizes human agency and ethical responsibility. These students remain critically aware of risks to integrity, equity, and learning quality, and they encounter uncertainty at epistemic, access, and institutional levels. Their adoption patterns reflect a nuanced and layered approach where enthusiasm and hesitation coexist, shaped as much by context as individual choice.

Connectivism helps explain how students integrate GenAI as part of their distributed learning networks, while CBAM Stages of Concern highlight the overlapping concerns that shape and complicate this adoption process. Together, these frameworks reveal that adoption is less linear than traditional models predict, characterized instead by multidimensional concerns, iterative experimentation, and discipline-specific variations.

The implications for higher education are significant—educators and institutions need to move beyond “ChatGPT 101” toward a comprehensive AI literacy and fluency that centers productivity, partnership, and ethical responsibility. Institutional policies must provide clear and equitable guidance across disciplines and ensure equitable access, positioning GenAI as an augmenting presence rather than a replacement. As one of the authors says to her classes, “If the robots take over, shame on us. We did not do what it takes to humanize education.” Ultimately, human relationships, critical thinking, and authentic intellectual engagement remain central to academic and professional growth.

Future research should continue to examine GenAI use across institutional types, degree levels, and cultural contexts to better understand how emerging forms of AI literacy are cultivated and sustained. Given the localized scope of this study and the evolving nature of GenAI integration, additional work is needed to evaluate how well current adoption models including the conceptual shifts within frameworks like CBAM's Seven Stages of Concern (e.g., the revision from “awareness” to “unconcerned”), account for the non-linear, rapidly shifting dynamics of GenAI use. Further research should also explore how institutional policy, instructional design, and equitable access shape learners' developing competencies, particularly in contexts that differ from those represented in the present study.

Declarations

Ethics Statement

This study was conducted in accordance with recognized ethical standards. Informed consent was obtained from all participants, and data were collected and reported with respect for confidentiality and anonymity.

The study protocol was reviewed and approved by the Institutional Review Board of New Mexico State University (#2502169200, 05/14/2025) for studies involving humans.

Informed consent was obtained from all subjects involved in the study.

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AI Use Statement

This paper was reviewed and refined with the assistance of OpenAI's GPT-4 and Anthropic's Claude, complementing the human editorial process. OpenAI's GPT-4 assisted with qualitative data analysis and earlier stages of drafting and editorial review. Anthropic's Claude assisted with final editorial refinement, sentence-level revision, and collaborative theoretical discussion related to the manuscript's conceptual framing. All AI-assisted content was reviewed, evaluated, and approved by the human authors, who take full responsibility for the accuracy, originality, and integrity of the manuscript.

Conflicts of Interest Statement

The authors declare no conflicts of interest related to the research, authorship, or publication of this article.

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Appendix A

Survey Instrument

Domain 1: What is/are your current role/s? (Check all that apply)

1. Graduate Student
2. Preservice Teacher
3. Inservice Teacher
4. Community College Faculty Member
5. K12 Teacher
6. University Faculty Member
7. Other

Domain 2: Prior Exposure and Program Context

- Prior to taking course/s from an online educational technology program, what was your experience with GenAI-related topics?
- Upon taking course/s from an online educational technology program that includes AI or GenAI-related topics, what do you remember about any AI or GenAI activities?

Domain 3: Awareness and Usage of GenAI

- Are you familiar with any of the following GenAI tools (list of 12 common tools provided and other option)? (Check all that apply)
- Please share which tools you are most familiar with and how you are using them
- How often do you use GenAI tools in your academic or professional practice? (Daily, Weekly, Occasionally, Never)
- For what purposes have you used GenAI tools (list of purposes provided and other option)? (Check all that apply)
- Do you have any intentions for future use of any of these or other GenAI tools and/or strategies?
- Is there anything these questions prompted you to think about and share that we did not ask in this section about tools and strategies?

Domain 4: Perceptions of and Attitudes Towards GenAI

- In your opinion, how helpful are GenAI tools in your learning or teaching practice? (Not helpful, slightly, moderately, very, extremely)
- Do you agree with the following statements?
(e.g., confidence, productivity, originality/creativity, academic integrity, institutional guidance)

Domain 5: Future Outlook in Regard to GenAI

- What potential benefits do you see in integrating GenAI into higher education?
- What challenges or concerns do you associate with the use of GenAI in academic settings?
- What, if any, trends in the use of GenAI do you see in your environment and/or field?
- What policies or practices (if any) does your institution have regarding the use of AI tools?
- As you move forward with your life, how do you see yourself using AI tools? What is trending for you?

Appendix B

Table 1

Alignment of Research Questions and Survey Domains

Research Question (RQ)	Survey Domain	Example Items
RQ1. What are the current trends in graduate students' awareness, experiences, and use of GenAI in academic and professional contexts?	Demographic and Professional Background	What is/are your current role/s?
	Prior Exposure and Program Context	Prior to taking course(s) ... what was your experience with GenAI-related topics?
	Awareness and Usage of GenAI	Are you familiar with any of the following GenAI tools? How often do you use them? For what purposes?
RQ2. How do graduate students perceive the benefits, challenges, and ethical boundaries of integrating GenAI into their learning and teaching practices?	Perceptions of and Attitudes Towards GenAI	In your opinion, how helpful are GenAI tools in your learning or teaching? To what extent do you agree with the following statements ...?
RQ3. What institutional policies, practices, and guidance shape graduate students' use of GenAI?	Future Outlook (Policy-related items)	What policies or practices (if any) does your institution have regarding the use of AI tools?
RQ4. What future intentions and outlooks do graduate students hold for the role of GenAI in their academic, professional, and personal lives?	Future Outlook (Intention-related items)	As you move forward with your life, how do you see yourself using AI tools? What, if any, trends in the use of GenAI are you seeing in your environment or field?

Transforming Enrollment Management in the Field of Online Learning

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Abstract

The landscape of enrollment management in higher education related to all modalities of learning is undergoing a significant transformation driven by evolving student expectations, shifting demographics, and the necessity for institutions to optimize operational efficiency. Traditionally centered on human-driven processes and relational strategies, enrollment management for online learning enterprises must now integrate advanced technologies such as Business Process Automation (BPA) and artificial intelligence (AI) to remain effective and competitive. This manuscript for online learning administrators and enrollment management leaders will explore the systems-level continuum from Business Process Mapping (BPM) to AI-driven functionality, highlighting the strategic evolution of enrollment operations within the field of online learning. BPM serves as a foundational tool to visualize, standardize, and assess workflows across recruitment, admissions, financial aid, and student communications. BPA streamlines routine tasks and enhances communication consistency. However, its effectiveness is constrained by static implementation and an inability to adapt to student-specific behaviors at scale. As we consider the use of AI in online learning enrollment management, we must explore the ethical considerations, data quality, system integration, and transparency of the operations. Institutions must establish governance frameworks to ensure the ethical use of AI, safeguard student data, and build trust in automated decision-making processes. The future of enrollment management for online learning programs lies in blending technological innovation with human-centeredness. Embracing AI within a BPA-to-AI roadmap pathway reinvents online learning enrollment management for online learning enterprises to thrive.

Keywords: Artificial intelligence (AI), online learning enterprise, business process management (BPM)

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Enrollment management within the field of online learning is the strategic art and science of attracting, enrolling, and retaining students to completion of goals or graduation. Traditionally, this function has relied heavily on human-driven processes, strategic communications, and relational management practices. However, the landscape of higher education is changing rapidly, influenced by shifts in demographics, expectations of prospective students, technological advancements, and competition from nontraditional education providers. Additionally, the need for institutions to do more with less by enhancing process efficiency is more critical than ever before.

Puntoni (2025) posits that generative AI is about human interaction, not about the technology behind it. To prepare for that type of interaction to occur within an enrollment management unit, steps must be considered for full functionality to be realized. Business Process Automation (BPA) utilizes technology to complete repetitive tasks that are performed frequently. The goal of using BPA is to reduce manual data entry and associated errors and allow staff to focus on the strategic decisions that need to be made to move the organization forward. Business Process Mapping (BPM) is the first step in moving toward BPA. BPM allows decision mapping to lead the efforts toward improving efficiency in enrollment management through automation of processes that can be done through integration of software in compiling, reporting, and disseminating data. Yet, in an age of artificial intelligence (AI), institutions are moving beyond the BPA processes. Staff are reimagining how to effectively work with the copious amounts of data being collected to better serve their students through the promise of AI functionality in conjunction with human decision making.

The purpose of this article is to explore the transformation from BPA to AI-driven functionality in enrollment management for online learning programs. Exploring a future environment where AI becomes a significant implementation tool in all enrollment management functionality will include definitions, challenges, opportunities, limitations, and case studies of institutions that have surpassed today's expectations as they use AI to enhance and improve their online learning ecosystems. As AI takes on more of the processing components of enrollment management, staff can spend more time on human interactions and personalization of communication with students and prospective students. More than ever, higher education institutions in general, and enrollment management units specifically, need to think differently about understanding business process automation and how mapping process to automation will lead to integrated AI technology to better serve institutions, students, staff, and faculty with a more effective overall experience.

Understanding Business Process Mapping and Business Process Automation

The first step toward improving efficiencies in enrollment management units is to develop collaborative cross-functional teams that will engage in conversations regarding business process mapping. BPM is the visual representation of an organization's workflows to analyze, document, and improve its business processes (Damelio, 2011). Implementation of BPM enables higher education institutions to map admissions recruitment and processing functions, financial aid, registrar and records functionality, and to develop hyper-personalized student communications for students seeking online degree programs. The adoption of hyper-personalized online student communications will be the competitive edge for institutions who successfully seek to use an AI-driven approach to communications. Creating the visualization through BPM for the functions that occur regularly in enrollment management allows institutions

considering initiating AI tools across the unit to prepare for implementation and to start utilizing chosen tools toward efficiencies early in the process (Cook & Kerr, 2023). In enrollment management, BPM has helped staff within the unit to identify bottlenecks in application processing, communication gaps between admissions and financial aid, and inefficiencies in lead conversion timelines and resulting yield. BPM also provides the opportunity to find systems that are not aligned, create stronger integrations, and to discover system breakdowns for correction.

Using BPM leads the institution toward use of business process automation. Key benefits of BPA in enrollment management include several increased areas for efficiencies. Cross-departmental interactions and communications are necessary to move forward with establishing business process mapping. By creating integrated functionality between departments, procedures may be standardized in a way that improves overall communication and process management. BPM encourages identification of redundancies and inefficiencies that can be eliminated or reduced across functional job lines. The departments and units within enrollment management find synergies through the work done to develop collaborative thinking to fully implement a BPA project through effective use of BPM. In my own institution, an ongoing BPM environment was implemented three years ago to move us toward continuous improvement in business process automation. These collaborative efforts resulted in significant reduction in manual entry between data input in the CRM to SIS systems.

Despite its usefulness, a traditional approach to BPA and enrollment management in the online learning enterprise faces numerous challenges. In today's environment, many institutions look for ways to scale online learning. Not only should the academic scalability be considered, but also the enrollment management functions. While BPA can assist in the day-to-day activities and processes, numerous challenges exist in fully implementing BPA into traditional enrollment management functions. Many processes within enrollment management units still rely heavily on manual data entry and data review, document analyses, and human follow-up on each process. This type of manual entry increases the likelihood of errors and delays, despite best intentions and technical expertise (Selingo, 2020). Departments, even within the same division, often operate in silos, leading to disjointed student experiences and miscommunication (Khosa, 2023). Continuous reviews of manual processes require significant time on task and expertise without guaranteeing transformative outcomes. This results in a decrease in the availability of staff to interact with students or to be engaged with students who have increased needs for personalized attention to their specific situations. Traditional workflows struggle to provide personalized engagement for prospective students at scale or in assisting students with specific situations. Students with multiple transcripts or first-generation students who need additional assistance with the college admissions process may stretch a manual service approach. Several environmental concerns make it difficult to address needs quickly through using a static approach to BPA. Environmental concerns that create challenges in the traditional approach of using BPA implementation include conditions such as quickly adapting to changing markets, unexpected and unforeseen enrollment drops, the demographic cliff in undergraduate programs, devaluation of higher education, and adjusting admissions criteria quickly to address specific program needs.

However, despite limitations, BPA can improve overall efficiency with enrollment management in several ways. First and foremost, BPA streamlines application workflows. Automation of standard communication such as requesting missing transcripts, sending

reminders, and answering standard questions received from students and their families can quickly be addressed through automated business processes. This standard workflow communication stream assists with the elimination of multiple staff addressing the same question. Reducing duplicated responses while simultaneously providing high-quality consistent messages in a quick timeframe can be satisfying for both prospective students and admissions staff. Creating a clearer communication path for students from first inquiry to enrollment through documented touch points adds to a positive student experience and assists with meeting the expectations of students in today's higher education environment. This approach provides the document tracking needed for student audits and financial aid compliance. However, efficiency gains through BPA alone are incremental and may fall short of the overall goal of initiation of new and innovative practices. BPA clarifies how things are done but does not inherently optimize the questions regarding whether an action would be done or why a particular action is carried out, nor can it respond adaptively in real time in response to individual student behaviors. Perhaps one of the most effective uses of BPM and BPA is to create a smooth transition pathway to use AI.

Even at their best, traditional enrollment management functions have fundamental limitations that result in less efficient operations and challenging staff expectations. Today, the trend is to open the top of the enrollment funnel by accepting as many applications as possible, whether the students are a good match for a particular institution and its online programs or not. Many online enrollment consultants push the idea that more applications will automatically result in more enrollments. Desperate enrollment-driven institutions sign on to increase the top of the admissions funnel. While this approach does increase inquiries and applications, the inquiries and applications will quickly outpace manual processing capabilities and may completely stall processes that were built for smaller application pools. Instead of increasing enrollments, this approach creates a backlog of students seeking entry that effectively blocks the enrollment funnel. Traditional methods of admissions recruitment and processing have typically been built on data from pre-Covid years. These data are not reliable today and are not able to predict student behavior accurately. This can lead to incorrect yield assumptions based on student behaviors such as viewing financial aid packaging or stop-out risks. Fragmented or siloed systems can prevent holistic student views across admissions, advising, and financial aid which will increase unequal treatment of students as their records become fragmented and possibly lost among systems.

Students who are comfortable with easy use of technology demand immediate responses in their shopping, social interactions, and family group texts. Students expect customized messaging that addresses their questions and is delivered quickly. Delivery of communications at scale, while necessary to meet the needs of students today, is impractical without automated support. Assessment and evaluation of enrollment management processes and operations are often based on lagging indicators such as post-matriculation surveys. This approach to evaluation of the operations inhibits proactive interventions. Finding ways to implement quick and immediate change is necessary for future success in enrollment management units that serve the online learning enterprise within an institution. Paying attention to what students think and want in real-time is essential to wise decision making.

To move toward the quality of high levels of student service in enrollment management functions, AI should be considered as an evolutionary tool that can assist with prediction of student behaviors from application to yield to graduation. Typically, institutions need to replace four to five incoming students for every student who is not retained to meet enrollment goals. AI can also be utilized to build better hyper-personalization communication funnels with perspective and current online students, assist in predicting use of tuition discounting, and help with building workflows and staffing metrics. Different types of AI can assist enrollment management units in completing the work needed to meet their goals.

Predictive AI is a data-driven approach that can analyze large datasets in relatively small amounts of time. Predictive AI uses machine learning algorithms to build predictive models. Many industries have used predictive AI for various functions for some time and to successfully build decision-making capabilities. Use of predictive AI in enrollment management for the field of online learning enterprises has been utilized at various scales and can assist with forecasting, tuition discounting, and financial aid leveraging as well as specific workflows.

Generative AI is often understood as being able to generate new text, videos, images, or other content. It also provides a predictive quality to an event that allows it to sequence communications or conversations. Generative AI is limited to being able to learn from human interactions and relies on pre-defined steps which may also be extremely productive within the enrollment management realm. Generative AI may assist with hyper-personalized communications and content generation.

Agentic AI can make autonomous decisions to lead toward specific state outcomes. It is adaptable to the environment in which it is being used without having constant human interaction. In enrollment management, agentic AI could be particularly useful in managing workflows and other decision-making capabilities based on circumstances. Agentic AI also requires extensive training and may not be able to function well on tasks that were not included in its initial training. The lack of information could lead to problematic situations and unintended consequences. Currently, agentic AI is an expensive initial investment, both to purchase technology and create the necessary training and on-going evaluation. It may assist with transcript review, articulation decisions, and optimizing recruitment efforts.

Enhanced Functionality of AI in Enrollment Management

To advance higher levels of student services and increase online enrollments, it is critical that strong predictions using multiple variables should be assessed and analyzed. AI can assist with analyzing retention for online students to increase overall retention and completion rates. Increased retention rates depend upon improved communication with timely interactions with online students. AI can focus on the automation of communication plans by using hyper-personalized messaging. As an example, Embry-Riddle Aeronautical University employs AI to identify students at risk of non-enrollment, allowing for proactive advising interventions (Jarvis, 2021).

AI analysis sets the stage for staff to increase individualized work with students by providing personalized counseling and mentoring. Several institutions have implemented generative AI in communication strategies, and several vendors currently offer multiple AI strategies to improve overall student communications. Many of these strategies were built using

the foundation of the technologies that developed the AI teaching assistant, Jill Watson, at Georgia Tech University. Jill Watson was developed by Ashok Goel, Computer Science professor at Georgia Tech (Design Intelligence Lab, 2025). The use of AI to augment the communication exchange with students provides a foundation for the enrollment management functions of the online learning enterprise to build strong student engagement throughout the enrollment funnel.

AI is also able to make staffing recommendations to admissions staff based on metrics of lead generation and staff strengths and abilities to engage with unique student populations. Through analyzing data related to individual counselor's and advisor's job functions, AI can assist with building out appropriate schedules creating higher productivity among staff (Upton, 2024). By using AI predictive analysis to review and determine data-driven insights, online learning enterprise-wide enrollment management units can make wiser decisions in the allocations of scholarships and institutional funded financial aid, when and where to develop market strategies, and determining matches to specific online programs in geographic regions. Predictive analysis from staffing to program markets can ensure the operations are moving smoothly and efficiently to promote increased enrollments.

AI-driven CRM systems such as Salesforce, Slate, and others predict the likelihood of a prospect's enrollment based on interaction patterns, demographics, and external datasets. AI can provide strong pathways to assist staff in determining student wants and needs based on a variety of behaviors. This is especially helpful when analyzing website and app interactions. By utilizing AI to adjust pathways for students and communications related to student behaviors, many student questions can be answered quickly and seamlessly without ever having to ask their question. Using Natural Language Processing (NLP) students can discover information through a chatbot regarding university processes such as application deadlines, scholarship deadlines, required documents, orientation schedules, program information, and career services hours. Georgia Tech's use of an AI teaching assistant, as discussed above, has set the stage for broader chatbot applications in university operations (GTPE Communications, 2016).

Challenges and Consideration in moving from BPA to AI Implementation

While there is much optimism surrounding the use of AI in enrollment management within online learning program units, several challenges and ethical considerations should be part of institutional conversations. Being cognizant of the challenges associated with BPA and AI implementation is a critical component of cleaning data and building out processes to ensure that AI is being used in a manner that will help and not hinder the university. Online learning enterprise leaders should develop team values that assist with the development of and implementation of strong ethical values that will guide the adoption of BPA-to-AI implementation across the online enterprise.

AI models are trained on historical data that may unintentionally perpetuate bias. Creating checkpoints and guidelines to review for algorithmic biases is critical to ensuring implementation based on automated processes (Floridi et al., 2018). Additionally, it is critical that data have been reviewed for redundancy, inconsistency, duplicate records and errors that will provide a clear picture of the student data record (Flaherty, 2024). There should be built-in transparency among the users to fully understand how AI models are flagging students as a likely yield and why AI is not identifying other students as potential to yield. Transparency in this

approach to determining which students receive which types of communication is an important consideration in decreasing the likelihood of bias or errors being developed in AI models.

All student and prospective student data must be handled with the utmost care. FERPA, GDPR, and PIPL regulations should be considered during development of data handling and policies. More countries will be reviewing and creating policies to better ensure student data is being handled ethically and with critical privacy. Data must be of high quality, and system integration will be key to the output. Data literacy for staff and for students is important. Data literacy and usage should be transparent and easily understood by students. Effective infrastructure is a critical aspect of increasing the use of data in ethical and meaningful ways (Flaherty, 2024).

AI can support four specific functions. First, hyper-personalization supports a dynamic communication process that is individualized to enhance the student experience. Each online student has expectations, individual needs, and a hope and desire for a successful career pathway after college. To help students feel known and heard, hyper-personalization can focus on each unique student and their needs. Second, optimizing marketing for increased ROI is a function that AI can effectively provide for a campus. Marketing functions within enrollment management drive yield. Third, AI can assist with the marketing functions by reducing the time that staff currently spend on repetitive data-driven tasks, including social media or content marketing. Fourth, AI can also be used to more effectively utilize the data contained within the CRM system in enrollment management. Having AI analyze data and provide actionable tactics toward a specific strategy is another use of AI within the marketing area of the institution. These AI-powered tasks can assist with increasing enrollments and thereby increasing revenues.

Through the use of the hyper-personalization related to marketing materials, student communication models can build continuous engagement threads from prospective students through graduation or completion and on into their journey as an alum. This continuous engagement using AI can build on known identities for responses and communications that support the student on each step of their journey and assist with scaling online programs. To make this continuing engagement possible, integrated CRM and SIS ecosystems must exist. Seamless integrations that provide the support for data exchange that can support the student throughout the lifecycle from student to alumni, to life-long learner. As AI continues to grow and develop, enrollment management and academic advising will increasingly overlap, allowing AI to assist students with finding correct online programs to meet their education and career goals. AI can also assist with providing continuing students with advisement and course scheduling. AI can provide information to connect career pathways into a variety of degree programs based on personalized goals. Setting student expectations for their post-higher ed careers is an area where AI can provide benefits to students from enrollment to academic advising to career counseling.

While BPA can be employed over time and with less investment prior to implementation, AI requires investment in platforms, training, and often customized development of models. The cost of AI should be considered as a strong investment for the future but, used well, will provide a path forward for enrollment management units in the competitive online learning market today. Staff will need innovative and forward-thinking leaders to assist with setting the vision for developing enrollment management models utilizing AI technologies. Staff will need training, as well as taking part in cultural shift conversations. Many may fear the BPM exercises are too complicated or require additional work prior to seeing long-term benefits. Many may fear that

BPA and AI adoption as management functions will diminish human interaction among staff and students or eliminate jobs (Floridi et al., 2018). According to Upton (2024), colleges and universities should establish and implement AI governance frameworks that will manage institutional risk, ensure transparency in use, and create high ethical standards in both policy and practice.

As AI evolves, its influence in enrollment management will deepen. Enrollment management units supporting online learning programs that are preparing for the future through building business process mapping and automation will be steps ahead toward AI integration into everyday functionality. By focusing on incremental steps, institutions will be able to fully utilize the promise of AI in deepening enrollment management productivity.

Future of AI Use in Enrollment Management

The future trajectory of AI in enrollment management is extensive. AI will continue to develop, and innovative enrollment management units will utilize these new technologies to reach new audiences and better serve continuing students. AI will also assist with retention and completion efforts, as well as provide models that continue to engage students with the institution, staff, faculty, and other students as they are supported through AI functions (Flaherty, 2024).

Institutions such as Maryville University are looking to the future as they begin utilizing AI to extract and interpret data from high school and college transcripts to assist admissions processing staff. This type of process management allows for more effective and timelier decision making for students. Future use and utilization of AI to read and interpret transcripts across institutions will be a significant support of a manual and often tedious function, especially related to transfer students who may wish to enter online degree-completion programs. This functionality will allow admission processing staff to spend more time in communication with individual students to ensure they enroll in the online program that best meets their educational and career goals. (Jaschik, 2023).

AI can also provide predictive analysis to better leverage financial aid. AI can change behaviors and thinking about the use of institutional or gift aid for online students by utilizing historical data. When predictive analytics are provided based on student data, institutions can better make decisions on how to most effectively utilize institution-based financial aid toward growing robust student yield (Upton, 2024). As AI grows and provides higher levels of functionality within higher education, ethical AI practices will be significant. Accreditation agencies and regulators will likely introduce AI-specific standards for higher education operations in the future. However, each institution should be a leader in the higher education industry by adopting strong ethical policies and procedures within their system-level enterprises including the online enterprise and beyond.

Conclusion

The transformation from Business Process Automation to AI-driven functionality in enrollment management represents both a significant opportunity and a complex challenge. BPM provides the foundation of clarity, standardization, and modest efficiencies, but AI promises a reinvention of enrollment management functions for the online enterprise by unlocking predictive power, automation, personalization, and dynamic decision making at scale. However, institutions must proceed thoughtfully, prioritizing ethical standards, transparency, and human

oversight. Enrollment management professionals who embrace AI while maintaining a human-centered approach will position their institutions for success in an increasingly competitive and volatile online learning market.

Declarations

I assert I am the author of this article and have no conflicts of interest to report.

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Educating the Educators About AI: Strategic Initiatives in a Graduate School of Education A Case Study

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Abstract

Much of the discourse about the implications of Artificial Intelligence (AI) for education so far has focused on what uses of AI should be allowed by students and instructors in current courses. However, as AI is changing the nature of jobs in most professions, including those within the field of education, an even more important question for schools of education is, “How can we prepare our students to successfully manage AI as education professionals in their future careers?” Over the past two years, our school of education has grappled with this question, which led to a comprehensive initiative that included developing our own internal capacity for AI, while at the same time drawing implications for our academic programs as well as our own practices as teachers and researchers. This article will report on both the outcomes of this initiative and the process the faculty went through, as we believe that the insights and lessons learned from this case may help other schools of education prepare for the inevitable disruptions AI is going to cause in all education professions.

Keywords: AI, education, graduate school, faculty impact, student experience, entrepreneurship, instructional technology, strategic initiatives

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While Artificial Intelligence (AI) has been around for a few decades, including several educational applications (as reported in literature reviews by Li et al., 2024, and Rizvi et al., 2023), the launch of ChatGPT in November 2022 (OpenAI, 2022) has brought to the forefront the potential – and risks – of AI for education for a few complementary reasons. At the beginning, attention focused mostly on the implications of students’ easy access to this technology for “cheating” (e.g., Adams et al., 2023, Dunningan et al., 2023). However, as more and more teachers and administrators have been using ChatGPT or similar tools powered by Generative Artificial Intelligence (GenAI) to relieve their administrative burden (e.g., Diliberti et al., 2024, HolonIQ, 2024), and powerful applications to support more personalized instruction (such as MagicSchool [MagicSchool Inc., 2023] and Diffit [Diffit Team, 2023]) have been developed, educators have started to recognize that GenAI may impact education in much more fundamental ways. Indeed, given the predictions that GenAI will transform most professional jobs in the future (e.g., Mervis, 2016, National Science Foundation, 2020), there is no reason to believe that educators’ jobs will be spared this fate.

Since a core mission of schools of education is to train the next generation of educators across a variety of professions, these developments mean that as education faculty and academic leaders, we need to ensure that our students are prepared for this new reality – and we need to do this quickly, given the rapid advances of GenAI technology and its educational applications. Furthermore, since GenAI is new to everyone, this calls for preparing faculty and academic leaders to sufficiently understand its potential, limitations, and risks, as well as its implications for specific educational professions.

Recognizing this need, for the past two years the Warner School of Education at the University of Rochester has been working on a comprehensive initiative (referred to as the “AI Initiative” hereafter) to both build internal capacity to inform decisions related to GenAI and its implications, and to rethink our current programs preparing teachers, educational leaders, education researchers, counselors, health profession educators, and other education professionals. In designing and implementing this initiative, we leveraged lessons learned from the school's launch of its first online offerings about a decade earlier, while also recognizing the unique challenges posed by AI. We believe that reporting a detailed reconstruction of our journey, based on the artifacts produced and collected along the way, will provide insights and examples that could be valuable for other schools of education facing the same situation.

To better understand this story, we want to provide some background information. The Warner School of Education is part of the University of Rochester (UR), a nationally recognized research university, serving more than 6,000 undergraduate and 5,000 graduate students. The smallest academic unit within the University, the school includes about 45 active faculty members and serves approximately 700 graduate students across doctoral, master’s, and advanced certificate programs. Despite its small size, the school offers programs in a variety of fields within education, including teacher preparation, K-12 leadership, higher education, education policy, counseling, human development, health professions education, program evaluation, and human development. Instructional programs are mostly managed by faculty in three main program areas: Teaching & Curriculum, Educational Leadership, and Counseling & Human Development.

In addition to program areas, the school also has four Centers that focus on specific areas within education. The most recent of these centers is the Center for Learning in the Digital Age (LiDA), founded in 2018 with the mission of “*Transforming education by leveraging digital technologies*” through a combination of engaging in research, promoting and supporting specific digitally-rich educational innovations, providing professional learning opportunities for educators, and serving as a catalyst for networking and collaborations around the topic (Center for Learning in the Digital Age, n.d.). The LiDA Center’s human resources consist of six individuals (including the two co-authors) who are partially funded by the Center, as well as ten additional LiDA Affiliated Faculty volunteering their time. Not surprisingly, the LiDA Center played a leadership role in the Warner AI Initiative from the very beginning.

Methods

Given the unusual nature of our study, we begin this section by identifying the complementary perspectives and experiences that most informed our work, before describing our study design.

Applying an Entrepreneurship Lens to Educational Innovations

The current Warner AI Initiative was informed by a previous initiative the Warner School engaged in, starting in 2013, to establish its first online courses and programs – referred to as the Online Startup Initiative hereafter and reported in a previous publication (Borasi et al., 2016). Since both initiatives represented major *innovations* for the Warner School, we chose to draw from the literature on entrepreneurship to study them.

As previously done for the Online Startup Initiative (Borasi et al., 2016), this meant first reconstructing how the AI Initiative developed so far with respect to the following key stages of the “entrepreneurial process” (Borasi & Miller, 2022), that is:

- Coming up with & refining the idea for the innovation
- Planning and gathering the resources to launch the initiative
- Implementing and monitoring the initiative
- Planning for sustainability

The following entrepreneurial principles have also been considered in our report and analysis:

- *Not feeling limited by the resources at hand* (Stevenson and Jarillo, 1990)—that is, the willingness to pursue a worthwhile innovation even if it requires creative ways to secure needed resources that the organization does not currently have.
- *Considering “missing the boat” risks as well as “sinking the boat” risks* (Brown & Cornwall, 2000)—that is, evaluating the potential consequences of *not* engaging in the

innovation, along with the chances of failing and the negative consequences of doing so.

- *Focusing on managing rather than avoiding risk* (e.g., Palich & Bagby, 1995, Busenitz, 1999)—that is, accepting the reality that any innovation will involve some risks, but those risks can be minimized by predicting potential risks and developing strategies to control them.
- *Accepting the need to make decisions with limited information* (Bygrave & Zacharakis, 2004)—that is, accepting the reality that most innovations call for making some time-sensitive decisions with incomplete information, and the willingness to compensate for it by monitoring outcomes on an ongoing basis and being ready to make any needed adjustments.
- *Securing a “champion” to lead the innovation* (Borasi & Miller, 2022)—that is, ensuring that the innovation is led by an individual with the drive to make the innovation successful, as well as the capacity and authority needed to make key decisions.

Key Principles for Instructional Technology Innovations

Innovations can be disruptive because new technologies make previously impossible ways of doing things possible. When these types of interventions occur in higher education, they often raise questions about potential changes in practices. Sometimes, the impact of concerns about the new intervention results in a desire to pause, slow down, or even stop the activity. This is not a new phenomenon in our colleges or universities. One might argue that this is a strength of higher education culture, where individuals can contribute to decision-making. And we have witnessed this kind of situation many times in our careers, especially the central role of faculty in academic or instructional matters.

In this article, we are connecting to our historical experiences with online education, so we would also acknowledge that we experienced this kind of questioning in the early days of that field. It was common for faculty and academic leaders to ask about the impact of that new, innovative way of offering courses. Does an online version of a course count for credit? Does an online version of a course count toward a degree program? Is the tuition for an online course different from that of a traditional, on-campus classroom course? Who decides who can teach an online course? What are the refund policies for an online course? What is the policy for withdrawing from an online course? Those are just a few examples, not a comprehensive and exhaustive list. But they do illustrate the potential to consider technology innovation as new and unique, and something that might have required new policies. We would also note that using precedents or analogies to the traditional academic activities is extremely helpful, because it is the same individuals who are making decisions about these new interventions.

Our guiding principle in the Warner School when we started offering online courses could be represented as the saying, “a course is a course is a course.” We were very conscious about NOT creating new policies for a new innovative method of offering courses. We tried to consider those questions through a lens that removed the modality. We took the technology out

of the equation and asked the same question. “Who decides who can teach an online course?” is then the same question as “Who decides who can teach any course?” “What are the refund policies for an online course?” is then the same question as “What are the refund policies for any course?” We would also acknowledge that this approach helps alleviate the need to explicitly define an online course. The dichotomy is difficult and somewhat arbitrary. Can an online course have any in-person meetings? If so, how many before it is no longer an online course? Where do you draw the line? If a course is a course, there is no line.

Recently, there have been discussions on campus related to AI technologies. One question is, “Can students use AI to write their papers?” We would adjust that question and ask, “Can a student use the efforts of someone else to write their papers?” If the answer to the second version is no, then we believe the answer to the first version would also be no. If the question was “Can a student use AI technology to correct the grammar in the paper they wrote?” we would ask a similar question as “Can a student use the efforts of another person to correct the grammar in the paper they wrote?” If the answer to the second version is yes, then we would believe the answer to the first version could also be yes. And in fact, our school offers writing support services to help our students in the writing process.

With regard to faculty, a question might be, “Can a faculty member use AI capabilities to help them design and develop content or activities for their course?” In that case, we might ask, “Can a faculty member ask a colleague to help them design and develop content or activities for their course?” If we are ok with the answer to the second version being yes, then we think the answer to the first version could be yes. Another question might be, “Can a faculty member use AI capabilities to grade and assess a student’s paper and provide feedback?” To help with this one, we might ask, “Can a faculty member ask a colleague to grade and assess a student’s paper and provide feedback?” If we think the answer to the second version is no, then it probably carries over as a no to the first version of that question.

So, as we are faced with new AI-related innovations and the questions that come with them, we believe this strategy can be beneficial. To help the community work through an analysis of those queries, we would suggest the same approach to remove the technology intervention from the situation and try to ask the same questions. This can help inform an appropriate response.

One last thought related to the consideration of questions that remove the technology innovation is that there may be times when it is difficult or when there is a special distinction that makes it challenging to answer the question at hand. Our advice in that case is not to wait for every question to be answered to begin something new; otherwise, you will never start anything. You really need to address the questions you understand at that moment in time. It is almost impossible to anticipate every issue in advance. Moving forward with the new innovation can be informative; you can learn more and improve your ability to answer the question or make a decision.

How Schools of Education Have Addressed GenAI So Far

We recognize that other graduate schools of education at other research universities have also been active with AI plans and initiatives. These efforts fall into a few categories. For institutional strategies, a recent study (McDonald et.al., 2024) noted that the majority of R1

institutions encouraged the use of AI in classrooms and many provided guidance and sample syllabi. A recent article in *EdTech* (Brereton, 2025) highlighted that other institutions have focused on faculty development, support, experimentation, and even faculty hiring in this new field.

Of particular interest are new curricula and degree programs. Examples of this include the Graduate School of Education at the University of Pennsylvania with their MS Ed in Learning Analytics and AI (Ng, 2024), the School of Education at UC Irvine now offers a Master of Education Sciences with a concentration in AI and Learning Analytics (UCI, 2025), and the College of Education at the University of Texas at El Paso launched a fully online Master of Arts in Education with a concentration in AI (UTEP, 2025).

It seems reasonable to expect more. The concept of institutional isomorphism (Sakib, 2020) would also support that. So, it may be prudent for graduate schools of education to consider planning and developing new programs in this innovative and expanding field.

Lessons Learned from the Previous Online Startup Case Study

Among the key lessons learned reported in the published case study of the Online Startup (Borasi et al., 2016), we identified the following ones as relevant to the AI Initiative as well:

- *Securing the needed resources and infrastructures—including support from the top:* School-wide initiatives that are potentially transformative require, from the beginning, support from the people controlling key decisions and resources. In the case of the Online Start-up, the dean (who was also the “champion” for this project) played a key role, as in the UR decentralized structure at the time, she was able to allocate the needed resources to hire some online education experts and compensate faculty investing their time learning about online teaching and redesigning their courses in an online format. Even more importantly, though, the dean was in a unique position to make the Online Startup initiative a priority for the school.
- *Securing students and faculty buy-in:* In addition to the dean’s support, the success of the Online Start-up also depended on both faculty and students’ acceptance of online learning as a viable and high-quality modality. A critical move to gain faculty and students’ buy-in was not to force anyone to teach/take an online course unless they wanted to, so the first online offerings were courses that were either electives or had multiple sections (so students had a choice about whether to take the course in the in-person or online modality) and were taught only by faculty who volunteered to do so.
- *Developing internal capacity to implement the initiative:* At the time, offering online courses was first considered, the school did not have any “online education expert” on staff, and only a handful of faculty had prior experience teaching online. To address this challenge, the dean first hired two part-time online experts to jump-start the initiative by modeling high-quality online courses and providing professional development to the faculty. Even more importantly, though, the counter-intuitive decision was made to concurrently launch a new Advanced Certificate in Online Teaching, to develop a cadre of interested Warner faculty, doctoral students, and adjunct instructors able to offer an increasingly rich list of online courses at Warner.

- *Developing new policies and practices related to the initiative to ensure long-term success:* Almost as soon as the Online Start-up was launched, a number of questions began to emerge that called for setting new expectations and/or policies. Addressing these issues upfront was critical to the success of the initiative.

These considerations informed several key decisions about the Warner AI Initiative, and in our reconstruction of how this initiative developed, we pay special attention to *what was put in place* to realize each of these conditions for success in this different case.

Case Design

Given the LiDA Center's interest in exploring AI implications for education as well as the authors' previous experience with the Online Startup, from the beginning we approached the AI Initiative as both a quality-improvement initiative and an opportunity to learn about "*how schools of education should respond to GenAI.*" Many artifacts were generated throughout the initiative – including memos, official documents, information posted on the school website, fieldnotes and summaries of key meetings and events, and publicly shared summary results of surveys (including one administered in Spring 2024 to gather students' perceptions about AI and one administered in Summer 2025 to gather faculty's opinions and feedback about the school's AI-related initiatives).

All this information was used to write a first draft of the "story" of the AI Initiative, which was then shared with several Warner faculty to verify its accuracy. A revised version of the story was based on the feedback received. We then used conceptual analysis to examine the story to see if and how the entrepreneurial principles identified in the literature review section were enacted in the AI Initiative, as well as to derive some lessons learned and recommendations for other schools of education.

Results

In this section, we report our reconstruction of how the Warner AI Initiative developed, using the four key components of the entrepreneurial process to structure our narrative.

Coming Up with and Refining the Idea for the Initiative

Following the launch of ChatGPT in November 2022, faculty and staff in the LiDA Center (who had already been exploring the potential of AI for education as part of the Center's mission) were immediately intrigued by what GenAI could do for education. Several individuals within LiDA began to individually explore the capabilities of ChatGPT as well as follow webinars and presentations on this topic. Most importantly, the need to have a dedicated person keep up with the new developments around GenAI applications to education and keep the other LiDA faculty and staff informed was identified, and the LiDA director was able to secure the financial support to invest in a full-time post-doc position to do so (using a combination of new gifts, existing grants, and existing Center's funds).

As a result of these preliminary investments and explorations, the LiDA Center came up with the ambitious idea of "making Warner the place to go for AI in education." The value of becoming a leader in this field was clear, given the potential of GenAI to radically challenge current teaching and assessment practices. The novelty of this topic and LiDA's previous

explorations about GenAI could also give Warner a competitive advantage in this area. The success of the Online Startup ten years earlier also gave confidence that the school could achieve – or at least work towards - this ambitious goal, despite not having much AI expertise in-house yet. We also expected that there was a big risk of being left behind if we did not engage with GenAI as a school of education now.

After a series of meetings to turn this initial idea into a concrete proposal, the LiDA Center articulated three key goals and components.

1. **Develop capacity within Warner to understand and leverage the potential of GenAI for education.** Since this is a new and rapidly developing field, we need to create opportunities to learn about possible GenAI applications and implications for education for Warner faculty, staff, and students, as well as secure a commitment to invest the time and effort needed to take advantage of these opportunities.
2. **Engage in exploratory research around applications and implications of GenAI for education.** Given that this is a rapidly emerging field, there is a big need for exploratory research to identify both the potential and risks of GenAI applications in various subfields of education, with new funding opportunities available to support these efforts. We want to be proactive in pursuing grant opportunities in this area, as well as in initiating internally-funded pilot projects to make us more competitive in securing the increasingly available external funding around GenAI.
3. **Provide professional learning opportunities for educators to learn more about GenAI.** While nobody can claim to be an expert in this emerging and rapidly changing field, educators have to make decisions NOW about the use of GenAI in schools and universities. Therefore, there is also a need for opportunities for learning and dialogue to inform those decisions – and Warner will be well-positioned to offer those opportunities as a result of work done within the previous components.

Given that this was an initiative involving the whole school, though, it was clear that the LiDA Center could not undertake it alone, but rather it would need to secure faculty support as well as approval from the dean. Therefore, the LiDA Center's director first presented and discussed the proposed goals and components with the dean in Fall 2023. The dean was supportive of the idea and charged the LiDA Center to develop a more detailed plan to be presented to the faculty. In addition, the dean appointed a new task force to oversee the implementation of the initiative. The AI Task Force included the LiDA Director (who had been the “champion” for the Online Startup as the former dean at the time) as chair, the LiDA Associate Director and Associate Vice-President for Online Learning for the entire university (who also played a key role in the Online Startup), the chair of the Faculty Steering Committee (in charge of setting the agenda and facilitating monthly faculty meetings), the Warner IT Director, and the dean's administrative assistant.

Planning and Gathering the Resources to Launch the Initiative

An initial list of possible interventions to begin to operationalize each of the three components of the AI Initiative was developed by the LiDA Center, informed by lessons learned from the Online Startup. This initial list included the following key initiatives:

1. Developing internal capacity:
 - a. Continue to invest in the dedicated post-doc position to keep up with the rapid developments in GenAI applications to education.
 - b. Dedicate some time at each faculty meeting to discuss AI-related issues.
 - c. Provide multiple and differentiated professional learning opportunities about AI for interested faculty.
 - d. Provide one-on-one support to Warner instructors interested in experimenting with GenAI applications in their courses by trained RAs.
 - e. Start a Warner GenAI policies & practices committee to examine potential issues and offer recommendations about using GenAI in courses.
2. Engaging in exploratory research:
 - a. Submit grant proposals related to GenAI applications to education.
 - b. Participate in university-wide research projects and initiatives around AI.
3. Providing professional learning opportunities for other educators around GenAI:
 - a. Design and offer new courses about applications and implications of GenAI within specific Warner programs and/or as an elective open to students from multiple programs.
 - b. Organize workshops/events for educators in the community.
 - c. Host a conference on GenAI implications for education.

As this initial list was shared and discussed with the AI Task Force, it was decided to postpone presenting it at a faculty meeting until we could engage faculty in small group conversations at the December 2023 faculty meeting about their “hopes and fears about AI”, related professional learning needs, and possible initiatives. At this faculty meeting, each small group was facilitated by a LiDA-affiliated faculty or staff member, who took field notes in Google Docs and made them accessible to the entire faculty for review and additions.

Among the key needs that emerged from the small group conversations were:

- Learning more about specific GenAI tools.
- Understanding how GenAI tools could help or hinder students’ academic writing.
- Discussing implications for Warner course assignments and assessments.
- Developing awareness of ethical issues around the use of GenAI.

- Knowing more about Warner students' uses of GenAI.
- Developing Warner-wide guidelines for uses of GenAI by students.
- Understanding implications of GenAI for K-12 schools.
- Benchmarking with initiatives taking place in the rest of the University and other universities.

The AI Task Force chair then created a handout that identified these key needs/desires and matched each with specific proposed initiatives that could help address that need. The handout was shared with the faculty along with a revised draft proposal for the key initiatives (based on the list reported at the beginning of this section), in advance of the January 2024 faculty meeting, where the proposal was discussed and received overall support from the faculty. As a follow-up, a final version of the proposal, which reflected the input received during the faculty meeting discussion, was created by the AI Task Force chair and sent to all faculty.

It is worth noting that no special funds were allotted to this initiative at the time. However, the initiative benefited from donations that had been previously secured for the post-doc position (which became even more critical to support many of the proposed initiatives), as well as a few new ones, and from a few existing grants related to AI educational applications. Most importantly, though, most of the proposed activities called for time volunteered by faculty – and the LiDA team in particular. The appointment of the AI Task Force by the dean was also significant as a visible signal that the initiative had the support of the school leadership.

Implementing and Monitoring the Initiative

The AI Initiative was officially launched after the January 2024 faculty meeting. This launch involved implementing most of the specific activities that had been listed in the proposal, as well as a few new ones that were developed in response to new opportunities. In this section, we report on just the most impactful activities that took place during the Spring 2024 semester.

First of all, multiple opportunities for faculty professional development were offered, taking into consideration individual faculty's different backgrounds, levels of interest, and preferences in terms of modality. The GenAI post-doc played a key role in organizing and presenting at these events, which included:

- A “basic” in-person workshop for faculty, introducing fundamentals of GenAI and its potentials and risks for education.
- Virtual presentations as part of the existing colloquium series.
- A “GenAI Study Group,” facilitated by the Gen AI post-doc, where, in monthly one-hour virtual meetings, she shared new developments in GenAI applications in education with any faculty and doctoral students interested in becoming “pioneers.”

The initial proposal of establishing a Warner AI policy committee was abandoned when we learned that our university was establishing university-wide committees to examine

implications and make recommendations about AI uses in research and instruction, respectively, and the AI Task Force chair had been invited to serve on both committees. Instead, the AI Task Force chair was asked to report back at faculty meetings on the progress made by these university-wide committees to inform Warner's decisions.

In March 2024, the GenAI post-doc and three doctoral students, supported by the LiDA team, designed and conducted an anonymous survey of Warner students to better understand their perceptions and needs about AI. This was one of the "needs" expressed by several faculty in the December 2023 conversations. The 113 responses received were analyzed by the post-doc and doctoral students, with only aggregated results being shared with faculty, as well as the LiDA team, to ensure full anonymity to the students who responded. Among the respondents, 92 reported already using AI for coursework, dissertation/thesis, and/or personal research projects. While a combination of benefits and risks was identified by almost every respondent, overall feelings about AI varied considerably, from a handful of students at one extreme who were very negative about any use of AI at Warner and a similar number of students at the other extreme who were strong advocates and begged the administration not to ban AI. Many students asked for more opportunities to learn how to use AI in effective and ethical ways.

In response, a few pilot initiatives to better prepare Warner students were initiated. One involved offering a new credit-bearing doctoral-level seminar on the implications of GenAI for language learning and instruction, designed and facilitated by a new faculty member with interests and expertise in this area, this course turned out to be instrumental for preparing about a dozen of doctoral students, who later served on AI-related grants and/or incorporated what they learned in their own dissertation—thus contributing to building Warner's internal capacity around AI and education. A 90-minute online session on GenAI implications for education was also designed and offered to prospective Warner students. We strengthened efforts (which had already started prior to the launch of the AI Initiative) to develop dual expertise in AI technologies and education for interested Warner doctoral students, as interested students were encouraged to pursue an Advanced Certificate in Data Science alongside their doctoral degree (four students took on this opportunity) and/or to participate in an NSF-funded training program around AR/VR (completed by six students to date).

While these learning opportunities about AI for Warner students already served the community (given that many of our students were practicing educators), additional professional learning offerings open to any educator in the community included monthly sessions of the LiDA Colloquium Series dedicated to addressing specific aspects of AI applications, and presentations at local events for K-12 educators. The latter included a half-day in-person retreat organized by the LiDA Center for representatives of the K-12 Digital Consortium (a collaboration of more than 25 school districts in the region), which involved more than 60 K-12 leaders.

All of the previous initiatives were informed by concurrent research around AI and education undertaken by groups of Warner faculty. This included:

- A project where a few Warner faculty explored a selection of AI tools (such as Synthesia and Microsoft Co-Pilot) as part of a university-wide mini-grant (University of Rochester Educational IT, 2025).

- An interview study to gather information about student affairs professionals' uses and perceptions of AI, conducted by a group of faculty and doctoral students (Barrett, 2022, Barrett et al., 2024, Barrett & Plate, 2024, Cui & Barrett, 2025, Plate & Barrett, 2024).
- An NSF RAPID grant awarded to a group of Warner faculty to study K-12 leaders' perceptions and experiences about AI, which produced an open-access online resource to support their future decisions about AI uses in K-12 schools (Borasi & Han, 2024), as well as several publications (Borasi et al., 2024, 2025, Mason et al., 2024, Miller et al., 2025, Vaughan-Brogan et al., 2024).

In addition, the AI Task Force chair also participated in the leadership team for a few interdisciplinary proposals involving multiple units within the university—a \$20M proposal for an NSF-funded AI Institute and an internal planning grant to prepare a proposal for an AI Horizons “transdisciplinary research institute.” Even though neither of these major projects ended up being funded, participating in these interdisciplinary grant proposals created unique opportunities to network and develop collaborations across the university, which later led to interdisciplinary grant proposals of great interest and value.

The most impactful events, however, took place during the 30-minute sessions dedicated to AI within each faculty meeting—as these sessions involved almost all faculty members, not just those who were already interested in the topic. Each of these meetings provided an opportunity to provide updates on the AI Initiative, introduce specific AI tools or applications, and, most importantly, have small group conversations on specific implications of AI for the school, facilitated by a member of the AI Task Force and/or LiDA, who took notes and shared them in documents made available to anyone on the faculty.

A few key strategies were employed by the AI Task Force in designing these critical sessions within faculty meetings. First, informed by the principles for instructional technology innovations identified earlier, faculty were asked to address specific issues that were emerging about AI (e.g., could students use AI when writing a paper assigned in a course?) by asking more general questions that did not involve the technology (e.g., what support could students use when writing a paper assigned in a course?). Second, we tried to separate applications of AI to support instructional design from uses of AI in teaching, as the CHLOE 9 Report (Simunich et al., 2024) suggested differences in faculty sentiments about these two applications. Third, rather than presenting faculty with new AI tools they would have to learn, they were made aware of AI features in tools they were already using - like the AI Design Assistant within Blackboard Ultra and the AI-enabled Generate Prompt option in Harmonize. Fourth, in one of these meetings, the chairs of each program area were asked in advance to report on discussions about AI taking place in previous program-level meetings, as a way to ensure that faculty in each program would grapple with implications of AI specific to their programs and research interests.

As a follow-up to the last faculty meeting, the AI Task Force chair shared with all faculty a summary document with links to more details and key information based on AI faculty questions. Faculty were then asked to review this document in preparation for the May 2024 faculty meeting, where the proposal was to be discussed and approved.

Proposal for Discussion at the May Faculty Meeting About Possible Uses of AI by Warner Students

1. (Starting Fall 2024) We will articulate in writing the acceptable uses of AI, and how they should be disclosed, in:
 - Each course (in the syllabus, to be decided by each instructor)
 - Each program milestones – such as comp exams and portfolios (as part of their written directions, to be decided by the program faculty)
 - Thesis/dissertation (Any proposed uses will need to be included in the proposal and be approved in advance by the dissertation/thesis committee)
2. (By summer 2024) We will create a document to ensure some consistency in how these decisions are reported + online resources for instructors to help inform these decisions
3. We will seek conversations with individual students about their uses of AI before making any accusation of academic dishonesty.
4. We commit to continue to learn about possible uses of AI and to share our insights and experiences

Change in Leadership and Its Implications

The planned discussion of the above proposal at the May faculty meeting, however, did not take place, as shortly before the meeting, an unexpected announcement was made that the current dean was leaving and that an external interim dean would start in July 2024. The AI Task Force felt that it was critical to secure the interim dean's support for the Warner AI Initiative before moving forward with any major initiative—especially when involving potential academic policies, curricular changes, or possible new courses/programs in AI for educators. Appreciating that the interim dean would need some time to better understand the school's priorities, the AI Task Force also decided to postpone conversations about the AI Initiative with the interim dean until the Fall.

In the meantime, however, work continued within the LiDA Center and small groups of faculty to explore GenAI tools and their potential applications, pilot some uses of GenAI in course activities, and pursue grant opportunities. The GenAI post-doc continued her exploration of educational applications to GenAI, as well as reporting in the GenAI Study Group meetings. The LiDA Colloquium Series continued to be devoted to topics related to AI. A few faculty began to include learning activities that made use of GenAI tools in their courses - as for example readings and discussions about AI's implications for higher education were added in the "Contemporary Issues in Higher Education" course, GenAI was used to create "interactive cases" in a course preparing school leaders, doctoral students in the introductory research methods course explored how AI could be used as a "thinking partner" when developing research ideas, and students in a teaching methods course for TESOL and world languages explored how they could use a variety of AI tools to support their students second language

development. Some program areas also set aside time and program-level meetings to continue the conversation about AI implications and share uses of GenAI in courses.

The award of an internal planning grant from the Provost's Office to prepare a proposal for an "AI Horizons Transdisciplinary Research Institute" also provided some unique opportunities, as a total of 19 Warner faculty, staff, and students were involved in this initiative. The Transdisciplinary Learning Series, organized as part of the planning grant, provided invaluable learning opportunities for all those involved. The white paper produced by the working group that focused on AI and Education was also instrumental in identifying valuable research ideas within this area. The AI Horizons website (Center for Learning in the Digital Age, 2025), which was created as a result, and includes links to the white paper as well as recordings of the Transdisciplinary Learning Series, represents a valuable resource for anyone interested in pursuing research in this area.

Another impactful event that took place in Fall 2024 was a faculty search that resulted in the hiring of the GenAI post-doc in a clinical faculty position, starting in July 2025 after the end of her current post-doc appointment. This new position was made possible through a combination of new donations and repurposing of LiDA Center's existing funds and provided a critical resource to continue some of the initiatives started in the previous years, as well as launch new ones.

Another important development during this period of time was the conclusion of the work of the university-wide committees discussing AI policies. Each of those committees produced guidelines for uses of AI in research (University of Rochester, n.d. a), instruction (University of Rochester, n.d. b), clinical practice, and communications, respectively, that were adopted by the university and made publicly accessible on the University webpage – along with a commitment of on-going review and updating.

Spring 2025 "Revival"

With the support of the interim dean, Spring 2025 saw a renewed attention to AI implications at the school level, focusing on two main goals: (1) supporting the implementation of the university-wide guidelines about uses of AI in instruction, and (2) preparing a proposal for a new Advanced Certificate in AI for Educators and Helping Professionals. Later in the semester, a rethinking of the support provided to Warner students for their academic writing in the age of AI was also initiated. Although efforts towards faculty professional learning and grant writing, as well as the post-doc explorations of new GenAI applications to education, also continued during this time period, in what follows, we chose to report only on each of these three key initiatives.

Developing and Communicating Expectations for Student Uses of AI in Courses

The university-wide guidelines for AI use in education (University of Rochester, n.d. b), as first published at the end of Fall 2024, required each instructor to make explicit to students what uses of AI may be allowed in each of their courses, as well as to take responsibility for promoting their students' AI literacy.

Develop Clear Course GenAI Policies

Instructors should create and communicate student GenAI course policies. The GenAI course policy should state when students must, may, or cannot use GenAI throughout the course

as a whole and, if applicable, any deviations from the overall GenAI course policy for specific course activities. The course policy should be communicated to students in writing and, for courses with a synchronous element, in class. When students are permitted to use GenAI, instructors should communicate in their course and assignment policy how students should document their use, verify the GenAI output, and attribute their GenAI use.

Foster GenAI Literacy and Ethical Use

In all teaching and learning contexts, instructors should not assume GenAI literacy but should provide GenAI literacy instruction to students and course staff such as peer educators and lab managers. Such instruction should include modeling responsible, discipline-specific use and discussing the strengths and limitations of GenAI, paying particular attention to inaccuracies, bias, and ethics. Instructors and students should recognize that GenAI outputs carry inherent biases due to the data used to train them and should take steps to avoid incorporating these biases into their work.

The need to follow these university-wide guidelines spurred new interest and urgency among the Warner faculty to get training and support for making and communicating decisions about the use of AI in their courses. Once again, some time was devoted at a faculty meeting for small group sharing and brainstorming around the topic of students' possible uses of AI in coursework and dissertations, with notes taken by a LiDA-affiliated faculty or staff member in each group, and then publicly shared. As a follow-up to these conversations, and in response to a specific request from several faculty members to get more guidance and support, the LiDA Center produced the following suggested language to include in course syllabi, which was first vetted with the AI Task Force and then presented to the faculty at the April 2025 faculty meeting. It would include a common statement and the identification of the approach to how AI can be used in the course, based on one of three options.

Common Statement

Consistent with UR guidelines for the use of AI in education, at Warner, we recognize that AI could provide valuable tools for our students, as long as it is used in ways that assist/enhance rather than replace learning. We also believe it is our responsibility to prepare future educators who can use AI effectively, safely, and ethically in their work, and who can promote such use of AI for the students they serve. This needs to start with ensuring that AI is used in appropriate ways by Warner students in all our courses, while also recognizing that what constitutes appropriate use will depend on the specific tasks students are asked to perform. Therefore, each course instructor is expected to determine when and how AI can be used in their course, and to make this expectation explicit to students.

OPTION 1: In this course, given its scope and learning goals, we chose to ask students to **refrain from using any AI tools unless explicitly allowed by the instructor for specific tasks.**

OPTION 2: In this course, given its scope and learning goals, students are **welcome to use AI tools to support their learning and completion of course assignments UNLESS specifically prohibited by the instructor for a specific task.** We expect students to use their judgment to ensure that their chosen use of AI supports rather than

replace/reduce their learning, and also ask that students disclose their use of AI in specific assignments, briefly describing how AI was used.

OPTION 3: The use of AI in this course will depend on the specific nature and goals of each assignment. Therefore, pay attention to the directions provided by the instructor for each assignment about whether and how AI can be used, and how that use may need to be disclosed and documented.

In addition, the LiDA Center also suggested a set of questions for instructors to consider when deciding which uses of AI to allow or even promote for specific assignments.

1. What are the learning goals for this assignment?
2. What are some ways we can imagine students could use AI to complete this assignment?
3. How would specific uses of AI affect the achievement of the learning goals for this assignment—and thus which of these uses would you want to encourage/discourage and why?
4. What directions would you like to give students about the possible use of AI in this specific assignment, and how?

A few written examples about how these questions had been used to make decisions about specific assignments were also provided. A customized chatbot was also created by a LiDA faculty to enable instructors to input their directions for a specific assignment, along with its goals and any additional considerations, and then interact with the chatbot to brainstorm and evaluate possible options in terms of possible uses of AI in that assignment, to eventually produce a text that could be used to communicate the decided-upon expectations to students. We thought that this customized chatbot might not only make this specific task less intimidating, but also provide some faculty with an authentic “experience as AI user”—which has been suggested by several K-12 leaders in the NSF RAPID project as one of the most powerful ways to enable educators to personally appreciate the potential, as well as risks and limitations, of GenAI (Miller et al., 2025).

The conversations around possible student uses of AI in their own courses were instrumental in renewing faculty interest to learn more about AI and its implications, as well as in questioning whether our current programs were still adequate to prepare students for their future jobs.

Launching a New Advanced Certificate and Its Curricular Implications

At the same time, mindful of how launching the Advanced Certificate in Online Teaching had been instrumental to developing internal capacity in the previous Online Startup initiative, it also seemed important to evaluate whether a similar program focusing on AI would be beneficial, and what it would take to develop one.

It was clear from the beginning that, in order to be successful, the launch of a new certificate, as well as a critical evaluation of our current programs preparing education practitioners and researchers in various fields, would need considerable faculty input and buy-in. Therefore, a key step was to organize a 1.5-hour faculty forum dedicated to these topics, which took place in March 2025. The agenda for this event was strategically designed to include a few inspirational presentations from key faculty in each program area who had made creative uses of AI in their courses, as well as facilitated group discussions by program area.

Faculty Forum's Plan:

- Framing & agenda overview
- Inspirational examples – brief sharing of specific examples of AI activity/ module already implemented in one of our regular courses (with speakers identified in advance)
- Facilitated small group discussions by program about: What students in that program should know about AI and its potential uses? Which of these goals could be achieved within existing courses? Which goals may require some “schoolwide” learning opportunities?
- Reporting back to the whole group
- Introduction to some initial ideas about an Advanced Certificate in AI for Education
- Small groups by program area to discuss these initial ideas as well as provide additional input about a possible Advanced Certificate
- Reporting back to the whole group

To identify a complementary set of examples of uses of AI in Warner courses to be presented at the faculty forum, interested faculty were first invited to participate in a preliminary 1-hour Zoom sharing session. A few faculty known to be exploring uses of AI with their students were individually solicited by the AI Task Force chair to come to this event and share their experiences. Concurrently, the AI Task Force chair secured the commitment of all program chairs to facilitate the small group discussion with faculty in their program that would be taking place as part of this Faculty Forum.

The faculty forum, which was held virtually on Zoom, was attended by about half of the Warner faculty, including all the program chairs. It generated thought-provoking conversations within each program about the potential implications of AI for the specific professions that the programs prepared students for. It was also instrumental to support and further refine the goals and structure for an Advanced Certificate in AI for Educators and Helping Professionals, leading to a proposal that was discussed and approved with a faculty vote at the April 2025 faculty meeting.

Proposal to the Faculty for a New Advanced Certificate in AI for Education

We are proposing a **new Advanced Certificate in Artificial Intelligence for Educators and Helping Professionals**, designed to prepare professionals across the various sub-fields of education and human development to become critical users of AI and to take a leadership role in ensuring that AI is applied in appropriate as well as effective ways in their field. [...]

In designing this new Advanced Certificate, we took into consideration the need to provide BOTH some common “foundations” that could be relevant to all Warner students, regardless of their specializations, AND opportunities to examine how AI may be applied in the context of one’s profession/field. We kept the number of credit hours to a minimum to make it more appealing to Warner students interested in adding this credential to their current program as well as to potential new students. [...]

The proposed new Advanced Certificate will involve a total of 10 credits to meet the following requirements:

1. One NEW required “foundational” course about AI & education (3 credits)
2. At least one courses relevant to their field of specialization that include significant components about AI and other electives related to AI (for a total of 6 credits)
3. A Capstone Experience, involving a project of the student’s choice where AI is applied to one’s field of specialization (1 credit)

The faculty vote was followed by a series of meetings involving the chair and selected groups of faculty in each program area, led by the AI Task Force chair, to gather information about possible AI electives within each program. As agreed, the AI electives would be existing courses to be redesigned to take into consideration the implications of AI for the topics covered in that course. These meetings were instrumental not only to identify a first set of AI electives to include in the new program application to the state, but even more importantly, to begin a deeper curriculum revision process within each program area.

The proposal for the Advanced Certificate in Artificial Education for Educators was submitted in summer 2025 to the New York State Education Department, approved in late Fall 2025, and launched in Spring 2026. The new required AI foundational course was designed and offered in Spring 2026 by the AI Task Force chair and the former post-doc, and 16 Warner students across multiple programs enrolled in this first offering.

Rethinking Support for Academic Writing

From the very beginning, Warner students’ use of AI in academic writing emerged as one of the most challenging and controversial topics. It was exciting when the Director of the Warner School’s Writing Support Services (WWS)—the entity supporting student academic writing at Warner through a combination of workshops and individual consulting sessions—reached out to the LiDA Center to collaboratively rethink how to best support academic writing in the age of AI.

Key players within LiDA and WSS gathered during the summer of 2025 to plan how the WWS workshop series may be revised in light of possible AI uses, informed by the reading of seminal works on AI and academic writing. They decided to create a new workshop to develop a general mindset about how to use AI to support academic writing in effective and ethical ways, as well as to redesign each of the existing WWS workshops to include considerations about appropriate uses of AI tools specific to the workshop topic. The redesigned WWS workshop series was offered over the following academic year.

Planning for Sustainability

As we are still at the initial stages of the AI Initiative and a dean search was taking place during the 2025-26 academic year, formal plans for sustainability have not been developed yet. However, the initial investments made towards developing the faculty's own AI literacy and hiring a clinical faculty with special responsibilities towards that goal, along with university-wide expectations and guidelines regarding the use of AI in instruction, are important foundations to ensure the continuation of this initiative.

As an important step towards sustainability planning, though, a survey of the faculty was conducted in summer 2025 to gather information about faculty perspectives on school activities and plans for AI, their experience with using AI in their teaching and research, and feedback about what they liked most and what could be improved regarding the Warner School's AI Initiative. While this effort was undertaken as a quality improvement initiative, not a formal research study, it did yield interesting data, with 64% of Warner faculty members responding. There was very strong agreement from faculty on the following, which suggests support for the AI Initiative's plan. (Note - Strongly Agree and Agree responses are combined for ease of reporting and discussion.)

- (96%) It was important for the school to develop a strategy and plan related to AI.
- (96%) It is important for Warner to develop internal capacity for AI applications for education
- (96%) It is important for the school to provide professional development and support to faculty.
- (100%) It is important for our students to develop skills and experiences with AI as future educators.
- (86%) It is important for faculty to consider adjusting the curriculum and their courses, given the impact of AI in their field.
- (82%) The sharing of syllabus statements regarding AI was helpful and resulted in a change to the syllabus for my course.

There were more balanced responses with respect to concerns regarding applications of AI for Teaching and AI for Research.

- (18% agreement vs 52% disagreement) I have concerns about using AI tools in my teaching.
- (25% agreement vs 43% disagreement) I have concerns about using AI tools in my research.

Faculty also reported on their preferences for the types of support they needed to integrate AI into their work. The top responses were “examples of how to use AI to support research efforts,” “training workshops,” “acquisition and implementation of technologies and tools,” and “examples of lesson plans, assignments, or interactive activities.” In a nutshell, the faculty responses to the open-ended questions were quite positive about the school’s initiative, and they appreciated the inclusive process.

Discussion

There are a few lessons to be learned from the story of the AI Initiative at the Warner School that may be of value for other schools of education grappling with the implications of AI for their organization—and possibly also for dealing with other future disruptive innovations.

The Importance of Considering and Managing “Missing the Boat” as Well as “Sinking The Boat” Risks

As it had been the case for the Online Startup a decade earlier, pursuing the ambitious goal of “Warner becoming the place to go for AI in education” involved a sizable risk of failing, considering the many uncertainties around the emerging field of GenAI, the small size of the Warner School, and the lack of experts in this area within the faculty at the time. However, the risk of “missing the boat” by ignoring AI’s implications for the field of education (because of not preparing our students well for the future and soon finding ourselves behind other schools that did make that investment) weighed more in the final decision of launching the AI Initiative than any “sinking the boat” risks we could identify. In making this decision, it helped to consider that an investment in AI was needed and would pay dividends in the future anyway, even if the goal of “becoming the place to go for AI in education” was not achieved. At the same time, awareness of possible “sinking the boat” risks led to strategic decisions to manage those risks such as hiring first a post-doc and then a clinical faculty member instead of establishing and searching for a new tenure-track position at first, as well as leveraging university-wide initiatives regarding AI.

The Challenges of Making Decisions and Setting Policies in a Time of Uncertainty

While online technologies for teaching and learning had been well established at the time the Warner School launched its Online Startup, the AI Initiative presented additional challenges because GenAI was so new, and technology advances were happening at such a rapid pace, that there were no established models to refer to, and even more importantly it was difficult to predict what AI tools may be available and what could be their affordances and limitations – and, thus, what could be the right decisions regarding what AI uses should be allowed by students and faculty. At the same time, it was clear that waiting to make any decision about such uses was not an option, as AI tools were already easily accessible to students as well as faculty. Therefore, it was important for the Warner School leadership to accept the necessity to make decisions about AI uses with incomplete information, which could potentially turn out to be wrong, and to

communicate the expectation that decisions about AI would need to be “temporary” and subject to change to all stakeholders. Equally important was the recognition that any of these decisions would need to be monitored and adjusted on an ongoing basis, and that the AI Task Force would be charged with doing so.

The Value of Addressing the Challenges Presented by New Technologies by Asking How Similar Situations Would Be Addressed Without Technology

In making several of the needed decisions around acceptable uses of AI, it helped to explicitly use the approach of asking more general questions about how the issue under consideration would be approached in the absence of the new technology. For example, turning the question of “is it acceptable for faculty to use AI as they develop content and activities for their courses?” to “what kind of help/support is acceptable for faculty to get as they develop contents and activities for their courses?” led to very fruitful conversations at a faculty meeting about how it is common and even encouraged for a faculty member to ask a colleague for advice about course design, although it would be considered unprofessional to ask a friend or teaching assistant to design a full course. This approach had some additional benefits, as it led faculty to share practices and assumptions about aspects of their practices that had not been discussed before, and in some cases, revealed conflicting beliefs as well as existing issues we had not even been aware of before.

Critical Roles Are Played by the “Champion” as Well as Other Key Decision-Makers

The story of the AI Initiative provides new insights about the role of the “champion” of an innovation as well as other key players—since in this case the champion was not in a position to make and implement many key decisions about the initiative (unlike what happened in the case of the Online Startup, where the “champion” was also the dean of the school, with a lot of autonomy about decisions about priorities and resources given the very decentralized nature of the institution). While the “champion” continued to play a very important role in moving the AI Initiative forward and designing opportunities for other players to engage in informed decision-making, policy decisions about how AI could be used in instruction were ultimately the dean’s (as long as they would be consistent with university-wide policies), and curriculum decisions about what students in specific programs should learn about AI, and how, were to be made by faculty in those programs. How meeting time should be used in school-wide and program-level faculty meetings was also decided by the Faculty Steering Committee and each program chair, respectively, so securing the support and involvement of these key players was needed. The commitment of the dean was especially critical, as made even more evident in this case by the “pause” caused by changes in leadership, even though both deans supported the initiative. It is also worth noting the important roles played by the LiDA Center (given its mission) and the AI Task Force appointed by the dean (which included members in critical positions to move the initiative forward, such as the LiDA director, the chair of the Faculty Steering Committee, the Associate Vice-President for online learning for the entire university, and the school IT director). In other words, we could observe much more of a “distributed leadership” model in the AI Initiative than had been the case in the Online Startup, which in turn made faculty buy-in of even greater importance.

Connections Between Gaining Faculty and Students' Buy-In and Developing AI Literacy

In the case of the AI Initiative, securing faculty and students' buy-in was not only critical (as it would be when introducing any instructional innovation), but also went hand-in-hand with the need to develop AI literacy *across the school* to allow for individuals' informed decisions as well as meaningful input for school-wide decisions. As previously described as part of the "story" of the AI Initiative, "developing internal capacity around AI" was identified early on as a key goal, on which the successful implementation of all the other components of the initiative would depend. A purposeful effort was made to provide multiple opportunities for professional development that would be appropriate for faculty at different stages of Roger's classic diffusion of innovation theory (e.g., Halton, 2023), from early adopters (through the GenAI Study Group meetings), to faculty who were interested but very new to the topic (through various *optional* presentations and workshops, as well as faculty forums), to faculty who were hesitant and even fearful of AI (and could only be reached at required faculty and program meetings). Across all these professional learning opportunities, the main goal was to make faculty aware of the affordances, limitations, and risks of AI for education, so they could develop informed attitudes that were both open and critical about this new technology. Multiple opportunities for faculty to express their hopes and fears about AI, as well as discuss implications of AI for their practices and their students, were also offered before presenting specific proposals, so as to ensure that those proposals would be informed by what the faculty had shared. Student buy-in was also considered very important, especially after hearing our students' conflicting opinions about AI from their responses to the 2024 survey, yet, looking back, this is a constituency that did not get as much attention as needed in the AI Initiative so far.

Developing Internal Capacity in an Emerging Area Requires Creative Solutions

Both the Online Startup and the AI Initiative have in common the decision to become excellent in an area where the current faculty did not have much expertise at the time – an example of "not being deterred by the lack of resources in hand," while putting in place strategies to deal with this limitation. The situation was different in these two cases, though, as while in 2013 online teaching and learning was a well-established field (so we were able to hire some external "experts" to lead the initiative and support the rest of the faculty), the launch of ChatGPT in November 2022, and the rapid advances in GenAI technologies and their applications to education since, meant that there were not many experts anywhere, and everyone had to develop the needed expertise at about the same time. As hiring an expert in AI was not an option, a key decision was to invest in a post-doc position to "keep up with AI advancements" and report back to the faculty interested in being pioneers/ early adopters, as well as play a key role in providing professional learning opportunities to the rest of the faculty. This (relatively minor) investment proved to be instrumental to the success of the AI Initiative. In both the Online Startup and the AI Initiative, the Warner School also made a strategic investment in developing some of our doctoral students' capacity to be "dual experts"–in new technology AND their field of specialization. We expected that doing so would not only benefit the field but also develop valuable resources to assist our faculty in both teaching and research applications of AI.

Value of Launching an Advanced Certificate as a Catalyst

In the case of the Online Startup, a key motivation behind launching an Advanced Certificate in Online Teaching was to quickly develop a cadre of high-quality online instructors for our own online courses, in addition to attracting students interested in this specialization to all other Warner programs. In the case of the AI initiative, we did not have the same need to develop

AI experts to perform direct services in the short term, but the second motivation held. What we did not fully appreciate until we started to discuss possible AI electives with program chairs and faculty, though, was that developing these AI electives could provide a very valuable catalyst for concrete discussions and actions around broader curricular changes in each of our key programs preparing education professionals in specific fields. In a sense, this mechanism served a role in providing non-threatening ways for faculty to consider adopting the new innovation, similar to the decision in the Online Startup to not impose teaching online to any faculty but rather start with just offering online sections for electives and courses with multiple sections.

Synergy Between Research and Instructional Decisions/Interventions

Finally, we would like to highlight the synergy that resulted from having LiDA staff and other faculty involved in exploratory research around AI applications to education, as well as considering instructional innovations related to AI. Engaging in this research served as a unique form of professional development for these faculty, which in turn impacted their contributions to school-wide discussions about curricular and instructional implications. For example, what the team involved in the NSF RAPID project learned about perceptions and uses of AI in K-12 schools provided many valuable insights about the potential and challenges of AI for K-12 education, which in turn informed the evaluation of what the K-12 teachers and administrators prepared at Warner should know, be able to do, and come to appreciate about AI (and how this could be best achieved in specific programs). Several of these insights could also be generalized to our own higher education setting, and were complemented by findings from the student affairs professionals' interview study that another group of faculty members engaged in. Participation in the AI Horizons planning grant also gave the many faculty who participated a better understanding of how GenAI works, its current limitations and issues, and the ethical and societal questions around its use.

Conclusions

The case of the Warner AI Initiative, as reported in detail in this article, shows that responding to the recent developments of AI will require schools of education to do much more than make decisions about whether or not to allow students to use AI in their schoolwork. Rather, it calls for questioning what appropriate uses of AI are for students *within specific courses and assignments*, as well as how faculty can be prepared to effectively and responsibly use these new technologies, along with the potential impact of doing so on current teaching and research practices, as well as professional identities.

This is not dissimilar to what happened with online technologies, so there are lessons that we can learn from the recent past. However, there are also some elements that are unique to AI, which will need to be taken into consideration. First, unlike most other instructional technologies in the past (including online technologies), in the case of AI, instructors do not really have control over whether or not *their students* may use it, given that AI tools are now easily accessible to everyone. As AI is affecting the workplace in almost all professions (including those within the field of education), schools of education are also called to re-examine how we prepare those professionals, which will involve not only pedagogical changes, but also curriculum changes—and we know that the latter tend to create greater challenges and resistance. Finally, the unprecedented rapid pace of development in AI technologies requires a different approach to decisions and policies.

From the study of the Warner AI Initiative, we have identified a few key conditions for success that we want to share with other schools of education—and possibly programs in other fields as well—to inform their respective plans for dealing with the implications of AI for their programs and organizations:

- The AI initiative should be explicitly identified as a priority for the school by the dean, whether or not the dean will act as the “champion” of the initiative.
- It is helpful to create an AI Task Force chaired by the “champion,” and give the chair sufficient autonomy and authority to implement the initiative, with clear backing from the dean.
- It is critical to engage ALL faculty in providing input to key decisions, to be informed by professional learning opportunities about AI that target faculty with different levels of interest and involvement, this should include providing some time at faculty meetings for professional learning and discussions, to ensure that even the most resistant faculty members are involved and informed.
- The investment in a post-doc or clinical faculty position, with significant time to be devoted to “keeping up” with advances in AI applications to the field and reporting back selected information to the rest of the faculty, will pay high dividends.
- Surveying students & faculty is valuable to get a pulse on the situation, and will need to be repeated over time, given the rapid changes.
- There can be great synergy between engaging in research to explore AI implications for education and leveraging AI for instructional innovations.

Finally, we encourage that all these suggestions be framed in an open and inclusive process. When we welcome faculty input and the corresponding variety of opinions and perspectives, we believe we will ultimately end up in a better place with these types of innovative initiatives.

Declarations

Institutional Review Board Statement This project was undertaken as a QI initiative, and, as per the University of Rochester’s Guidelines for Determining Human Subject Research, it did not meet the definition of research under 45CFR46.

Conflicts of Interest The authors declare no conflicts of interest.

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Section II

Editorial: Reasserting Epistemic Agency in the Age of AI

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I recently attended the American Education Research Associations (AERA) annual conference in Los Angeles, California. While there, I was able to reconnect with old colleagues and students who I have known for many years but have only interacted with via zoom (always a bit strange). I was also able to discuss our ongoing collaboration with the AERA Online Teaching and Learning SIG to publish papers presented within the SIG. Finally, I was also invited to present on a panel at the OTL Business Meeting.

The SIG is quite well organized, and organizers even sent out questions for the panel in advance of the session. As do all discussions these days the panel veered into questions on AI, and one of the questions was about the future of “good” online learning in the age of AI. More, specifically we were asked to provide a positive view of online learning five years from now considering ongoing developments in AI. I might have missed it, but this was not a question I had prepared to answer, and the time horizon stymied me. Five years in normal technology times is not the same as five years in AI time.

At the time, I made a joke about predictions being hard, especially about the future (Berra, 1959*). If we are to take such a question seriously though, there is much to consider. How do people learn in the presence of AI? How does AI potentially undermine learning?

In response to the question, I followed up with the observation that humans have been making use of linguistic tools for exceptionally long time. It may be that the extensive use of verbal symbolic interaction is the defining trait of the human species. Large language models associated with generative AI seem to be the latest advance in such tool use. However, language itself may go hand-in-hand with the origins of homo sapiens (Bickerton, 2012), the niche we occupied may have been founded on our initial advances in oral language use and the competitive advantages it provided to an animal that was able to collaborate flexibly and at scale (Harari, 2024).

Some scholars suggest that we have been using oral language for 250,000 years or more. Written symbol systems go back only 10,000 to 12,000 years and chirographic (handwriting) culture was dominant until the printing press in about 1453 and for decades after. Between 1453 and 1969 only 516 years passed before the moon landing (an achievement that required flexible collaboration at tremendous scale). The use of language tools appears to be accelerating cultural change in dramatic fashion.

To summarize we have had perhaps a quarter million years of oral language, 12,000 years of written language, 500 years of printed language, 60 years of digital language, 18 years of smart phones and social media**, and about 3 years of large-language-model based generative AI in wide use. Again, acceleration seems a defining trait. How can we responsibly predict where this

latest development in linguistic tool use will take us? Especially in the field of education, which is perhaps another species-defining feature.

So back to the original question, where is “good” online education headed in the age of AI? Extraordinarily complex questions require that we use all the tools at our disposal. We need a theory. Fortunately, my colleague, Jianwei Zhang has such a theory, which he calls “Intellectual Stewardship” and which is presented in a pre-publication here: [Intellectual Stewardship: Re-adapting Human Minds for Creative Knowledge work in the Age of AI](#).

Jianwei argues that in the age of AI we will need to cultivate new dispositions now and for coming generations. He indicates that these new attitudes can be thought of as aspects of human wisdom. We will need to teach people who use AI in education to be knowledge-wise, context-wise, intelligence-wise, and ethics-wise in the service of individual and collective intellectual growth.

Being *knowledge-wise* means attending to what you know individually and to the knowledge that that we share with others (language, theories, books, mathematics, scientific ideas, culture, institutions, collective knowledge). We train students to be critical consumers and (especially PhD students) to become contributors to such new collective knowledge. However, we can train all students to participate in the epistemic processes that result in more widely recognized artifacts of say, authentic disciplinary investigations. Advocates of Knowledge Building (including Jianwei) see learners at all levels as capable of participating in the production of new knowledge, not only new to the individual, but also new to the community.

The article warns that overreliance on AI can encourage superficial understanding and “cognitive offloading.” We can head this off by cultivating an *intelligence-wise* orientation including “meta-intelligence”, the capacity to decide when AI should assist thinking and when deeper human reasoning is required. Through this lens, humans must remain responsible for framing problems, judging quality, and directing inquiry.

Learners must also understand the social, cultural, and situational context in which knowledge work occurs. AI systems lack embodied, lived experience, and cannot fully interpret the meaning or significance of human situations. It is therefore necessary to cultivate *context-wise* dispositions among students. In a context-wise setting, students and teachers must identify (interest-driven) authentic problems, recognize emerging opportunities, and adapt inquiry to changing conditions.

Because AI can rapidly generate persuasive but inaccurate or biased content, ethical discernment becomes essential. *Ethics-wise* stewardship, foregrounds moral judgment, responsibility, and care. Learners must learn and value not only whether AI can perform a task, but also whether it should. Jianwei’s article emphasizes that ethics cannot be treated as an external rule system; ethical thinking must be embedded within everyday knowledge practices.

Finally, AI should not simply help students complete tasks more efficiently; it should support personal growth, deeper understanding, and contributions to collective well-being. The final and overarching form of wisdom is *self- and community-growing* stewardship. This principle gives

purpose to all others. The article repeatedly stresses that education should orient AI use toward long-term human flourishing rather than short-term productivity gains.

Back to the question of what “good” online learning in the age of AI will look like in five years. Innovative work in this area recognizes the need to change the culture of schooling as discussed above. Furthermore, the narrative around the uses of AI to improve efficiency need to give way to a recognition that the threat of AI to undermine productive cognitive struggle requires a new emphasis on human-focused epistemic agency. In the words of one of our doctoral students “What is missing is a close examination of the micro-level teacher-AI interaction processes through which teachers cultivate critical AI literacy regarding how they prompt, reflect, regulate, and iterate in authentic instructional contexts. (Zhao, p. 28).”

In other words, for online learning (or any learning really) to survive AI we will need to better understand how educators negotiate the moment-by-moment decision making processes that constitute a new form of AI literacy in AI-mediated design, teaching, and assessment environments. As it stands, we are insufficiently focused on who is in control when AI is used (and when it needs to be humans). The stewardship model is the first framework that articulates specific forms of human wisdom that identify explicit points at which we may need to reassert our epistemic agency. This kind of re-adaptation involves the whole culture of education. While unlikely to see broad scale uptake in five years, I think online learning would be better positioned for success if scholars, educators, and learners were engaged in a discussion of a stewardship model for AI in education. Culture change is difficult, but the primacy of human needs, growth, and flourishing demands this re-orientation. The risk of ceding human agency to AI in education spaces is not an option.

*The line is widely attributed to Yogi Berra (Lawrence Peter "Yogi" Berra; 1925–2015) but its precise origin is unclear — he popularized it, but evidence shows the joke existed earlier (attributed to Danish sources and Niels Bohr). There is no reliable record of the exact date or place Yogi Berra first said it. This approximation is courtesy of Duck Duck Go’s built in AI abilities (I didn’t know they had one till I tried to look up the origin story). However, the idea that Berra, a professional baseball player, manager and author of many paradoxical expressions, stole a line from a Danish physicist does make sense, I guess.

** As a species, increasingly, some observers note successive generations are being “rewired” by digital tool use (Haidt, 2024) with catastrophic results.

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Developing a Video-Based Discussion Platform with Emotion Detection Deep Learning to Increase Online Learning Engagement

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Abstract

This study discusses the development of Videmo platform. Videmo is a prototype online learning platform grounded in the Community of Inquiry framework and andragogical principles. It integrates Video-Based Discussion (VBD) and Emotion Detection Deep Learning (EDDL) technology to promote deeper learning and emotional engagement. Videmo Platform is a response to the limitations of Text-Based Discussion, which often miss capturing the students' emotions needed for interaction and understanding. Videmo recognizes emotional expressions such as happy, sad, angry and surprise using EDDL technology through facial analysis in videos discussion. Technical test results showed that the platform achieved an F1-score detection accuracy of 95% for MobileNet V1 SSD, followed by Tiny Face Detector F1-score of 92.0% and Face Expression Model F1-score of 88.0% in various lighting conditions and viewing angles. Surveys with 34 students found 86.27% of students said that Videmo engaged them more in the discussion and 75% of lecturers felt they understood the students' emotional engagement better. These findings illustrate the ability of Videmo Platform to transform the online learning experience into one that is more interactive and personalized. These initial findings suggest that Videmo may enhance social presence and provide instructors with richer insights into learner engagement, indicating potential for creating more interactive and personalized online learning experiences.

Keywords: Video-based discussion, emotion detection, deep learning, engagement, online learning

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In the digital age, online learning has become a core aspect of education, particularly after the COVID-19 pandemic, which forced numerous online learning platforms to be launched in many parts of the world (Almahasees et al., 2021; Camargo et al., 2020; Zhang et al., 2022), including in Indonesia. The platforms that enable online learning, not only allow better access to educational content but also can potentially facilitate the collaborative nature of teaching and learning (Almahasees et al., 2021; Camargo et al., 2020). A study by Musthofa et al. (2024) stressed that although teachers in Indonesia have been open to adopting online learning technologies during the pandemic, a gap still exists in optimizing these technologies to design effective and personalized learning for their students. Personalized learning involves not only tailoring academic content to individual students, but also supporting their emotional and social needs during the learning process. This support is especially critical in online environments where physical presence and face-to-face interactions are limited. Thus, there is a growing need for online learning systems that can respond to the social-emotional needs of users, particularly in online learning systems where physical interaction is reduced.

Most online learning platforms still rely on Text-Based Discussion (TBD), which many times misses out on the nuances of emotions and non-verbal communication. On the other hand, these components of emotion and non-verbal communication play an essential role in facilitating understanding and motivating learners regarding learning (Farsani et al., 2022; Mendzheritskaya & Hansen, 2019). Emotional engagement is an essential dimension of student engagement, and is recognized as a key component that can help create quality and impactful learning environments by having a strong effect on students' motivation, satisfaction, and learning results. Emotional engagement refers to the positive and negative emotional responses students exhibit during learning activities, including curiosity, joy, boredom, and worry (Fayanto et al., 2024). By recognizing and addressing these emotional dimensions, educators can create learning environments that are more supportive and personalized. The use of technology that supports non-verbal interaction in online learning is significant for developing adaptive learning environments. The technology integration in 21st-century learning is essential to foster students' soft skills and adaptability, enabling more engaging and effective classroom experiences. It had been demonstrated that technology-enhanced environments in learning contribute greatly to the critical skills needed for modern education (Oktaviani et al., 2019).

To ground this study, adult learning principles offer an essential theoretical perspective. Knowles' (1984) andragogical approach states that adults learn best when they are self-directed, goal-oriented, problem-centered, and have a clear understanding of how the learning experience is directly related to their professional or personal context. They bring previous experience as resources for understanding, interpreting new information, and constructing meaning. In the context of online learning, these characteristics suggest that an online platform must offer more than content, it must provide autonomy, relevance, and opportunities for active participation. Research on student initiative and engagement in online environments suggests that when students are afforded autonomy and can contribute meaningfully, their cognitive and affective investment rises, thus resulting in more positive learning outcomes (Heflin & Macaluso, 2021; Martin & Bolliger, 2018). Videmo addresses these needs by allowing learners to take part in asynchronous Video-Based Discussions (VBD), allowing them to respond in their own time, and to make a meaningful contribution to the collective learning experience. This design also is congruent with the online engagement frameworks that emphasize social presence, learner agency, and emotional connectedness as core dimensions of quality learning experiences

(Redmond et al., 2018, 2023). Moreover, the integration of Emotion Detection Deep Learning (EDDL) enables Videmo to provide emotion-sensitive information about learners' affective states during video-based discussions. This information can help instructors better understand students' emotional engagement and provide more responsive feedback. In this way, Videmo has the potential to support a more personalized and supportive online learning environment. Recognizing and responding to emotional presence has been shown to lead to stronger online learning communities and participation (Jiang & Koo, 2020; Lowenthal & Moore, 2020), and further validates the justification for EDDL inclusion in Videmo. This also accords with Media Richness Theory (Daft & Lengel, 1986), which argues that rich media such as video are more effective for complex communication, and with Social Information Processing Theory (Walther, 1992), which claims that meaningful interpersonal connections can be developed online if enough social cues are available.

To address this issue, we created an online learning platform called "Videmo" that uses Video-Based Discussion (VBD) which is also equipped with emotion detection feature based on Emotion Detection Deep Learning (EDDL) technology. With emotion detection, Videmo delivers a personalized experience that provides the student a more meaningful discussion. This level of personalization is in line with the research of Ulfa et al. (2024), which develops adaptive instructional scaffolding on online discussions to support personalization and enhance engagement in MOOCs learning environments. Adaptive Instructional Scaffolding refers to a dynamic support mechanism in online learning environments, where instructional assistance is adjusted based on learners' individual needs, cognitive progress, and even emotional feedback. This approach allows students to receive timely guidance, explore multiple perspectives, and stay engaged in meaningful ways throughout the learning process. Adaptive Instructional Scaffolding is a great way to encourage students to explore, analyze, and understand diverse perceptions and to be challenged in their learning with a more in-depth understanding of their learning space relevant to Videmo's aim to be adaptive and emotional in their video-based discussions.

In this study, Videmo was specifically applied in the context of asynchronous video-based discussions, where students respond to online discussion by recording and uploading video. This context emphasizes student autonomy and the opportunity to express ideas through verbal, facial, and emotional communication. Through Videmo, students can give feedback via videos recorded directly on the platform, while EDDL technology automatically detects students' expressions during video recording. Videmo is a video-based discussion platform that allows content sharing, but it also detects and displays students' emotions during online discussions. It is crucial to employ EDDL technology in online learning because emotional expressions of students often reflect their understanding, motivation, and engagement about a specific subject (Mercer, 2019; Cheng et al., 2022; Ekström et al., 2020). The evidence is clear that positive emotions play a crucial role in maintaining motivation and attention, resulting in better learning outcomes over time (Dao & Sato, 2021; Denovan et al., 2020; Reinhold et al., 2021). Videmo bridges the gap for richer interaction during online learning using deep learning-based emotion analysis technology. This technology can recognize seven primary emotions such as happiness, sadness, anger, surprise, neutrality, fear, and disgust captured from students' facial expressions in discussion videos. This analysis enables instructors to provide more personalized feedback and gain deeper insights into students' emotional involvement during online discussions. In this way, Videmo offers a more holistic approach to online discussion by combining video-based interaction, discussion content, and emotion analysis.

The purpose of this study is to investigate how Videmo's features, specifically Video-Based Discussion (VBD) and Emotion Detection Deep Learning (EDDL), enhance student engagement and understanding in online learning environments. This study also evaluates the accuracy of the emotion recognition technology under different usage conditions and examines user satisfaction with the integrated VBD and EDDL features. Based on these objectives, this study addresses the following research questions:

- RQ1: How effective is the Video-Based Discussion (VBD) feature in Videmo at enhancing student engagement in online learning?
- RQ2: How well does the Emotion Detection Deep Learning (EDDL) technology detect key emotions (such as happiness, sadness, anger, surprise, neutrality, fear, and disgust) from students' facial expressions in Videmo?
- RQ3: What is the satisfaction level of instructors and students regarding the emotion analysis feature in Videmo in supporting evaluation and feedback processes in online learning?
- RQ4: What technical challenges does Videmo face in implementing emotion detection, especially in relation to variations in lighting and facial viewing angles?

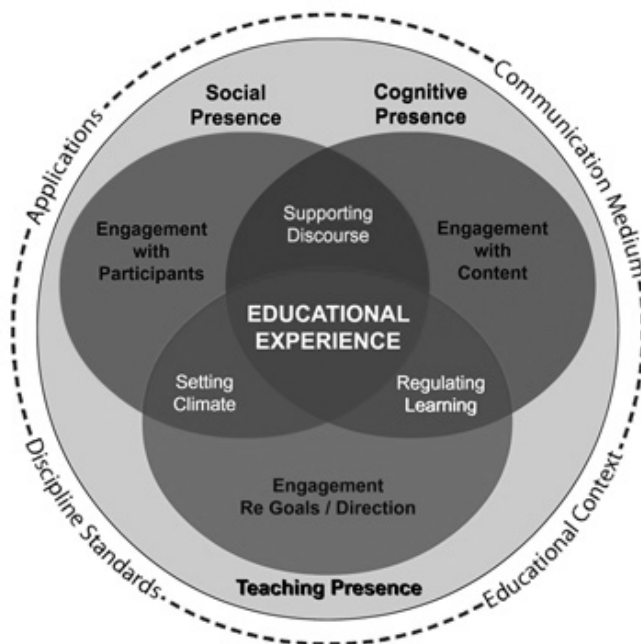
Through these questions, we hope this research will help advance current online learning technology, especially in establishing a more interactive and personalized learning environment among the students.

Literature Review

Video-Based Discussions in Online Learning

The online education literature identifies Video-Based Discussion (VBD) as an effective approach to increase student engagement. VBD allows students to give expressions, feelings, and body language directly, adding an element of communication that is harder to establish in a discussion that is only text-based. Milovic and Dingus (2021) showed that video-based discussions allowed students to feel more connected to classmates and lecturers and the interaction felt more meaningful. These findings demonstrate that VBD was able to mitigate isolation, an emotion prevalent in online learning, and heighten social presence, which contributes to the construct of inclusive learning.

Video-based discussions (VBD) offer a rich communication environment with the availability of verbal and non-verbal cues, which is consistent with Media Richness Theory (Daft & Lengel, 1986). The theory argues that rich media, in this case video, are more effective than text to convey socially complex information. In addition, Social Information Processing Theory (Walther, 1992) posits that interpersonal connections can become meaningful when relational messages are conveyed effectively in online communication. In the context of VBD, these relational cues include facial expressions, tone of voice, eye contact, and visible gestures. Recent studies have confirmed that VBD increases social presence, mitigates feelings of isolation, and enhances learner satisfaction (Milovic & Dingus, 2021; Swartzwelder et al., 2019). Research on learner presence and online engagement also emphasizes that social presence and emotional presence of the learners are key predictors of engagement, making VBD a critical strategy for online education (Jiang & Koo, 2020; Redmond et al., 2023).

Figure 1*Model Community of Inquiry (CoI)*

Social presence is vital for the creation of an effective-learning experience according to the Community of Inquiry (CoI) model (Garrison et al., 1999). This model places a great emphasis on non-verbal modes of communication, including facial expressions and body movements, in developing positive social interaction in online educational settings. While applying CoI provides an opportunity for students to interact more deeply - helping to promote an inclusive and participatory learning environment (Syarifuddin et al., 2020). Compared to other theories such as Social Constructivism or Self Determination Theory, the CoI model offers a more structured lens for understanding how social presence and cognitive engagement work together in online learning settings. This theory is particularly relevant for Videmo because it emphasizes the importance of non-verbal communication, emotional cues, and social presence, all of which are enhanced through video-based discussions (VBD).

VBD inherently caters to this aspect of communication, enabling lecturers and students to share richer and more affective messages than they did in text. Swartzwelder et al. (2019) found that video-based discussions increased student engagement and interaction compared with text-based discussions. In particular, students who participated in video-based discussions were more willing to contribute, respond to peers, and communicate their understanding of the discussion material. Similarly, Lowenthal and Dunlap (2010) argued that virtual presence can strengthen the emotional connection between learners and instructors. Video-Based Discussion (VBD) can therefore stimulate social interaction in online learning settings by giving learners a way to express their thoughts and feelings through video, which may serve as an initial step toward deeper cognitive engagement.

The Importance of Emotions in the Learning Process

Emotions play a pivotal role in learning, and even more so in the context of online environments, where face-to-face interaction is restricted. Positive emotions, such as excitement, motivates and engages the student, and negative emotions, such as anxiety or frustration, detracts from learning according to the Control-Value Theory of Achievement Emotions by Pekrun (2006). Detecting emotions is critical in these online learning contexts for measuring the students' engagement, and allows for timely instructor intervention. The Control-Value Theory by Pekrun (2006) was selected because it explains the causal relationship between perceived control, value appraisals, and achievement emotions. Unlike basic motivation theories, the Control-Value Theory directly addresses how emotion influences learning outcomes. In Videmo, emotion detection is framed through the Control Value Theory to identify how students' emotional states such as anxiety or enjoyment reflect their perceived mastery and engagement. Research by Immordino-Yang and Damasio (2007) further evidence that emotional engagement in learning improves recall and strengthens memory of learning subject matter for the long term. Their study found that positive emotions can enhance learning resilience, increasing the retention of information over long periods of time. As a result, in the scenario of online education, technologies that can determine and modify emotions can significantly assist in facilitating personalized and adaptive learning experiences (Calvo & D'Mello, 2010).

Emotions during online learning always reflect important signals about students' cognitive activities. According to Artino (2012), emotions like confusion and frustration are good early indicators in understanding whether or not students are having difficulty with parts of the material. When instructors are aware of how their students are feeling, they can better tailor their support to the areas that need it most, in a timely manner.

Affective learning theory highlights that emotions influence attention, motivation, and memory, and thus how they impact learning depth (Bloom & Krathwohl, 1956; Immordino-Yang & Damasio, 2007). In online learning, where physical presence are limited, encouraging emotional presence can be important in maintaining participation and preventing disengagement. According to Redmond et al. (2023), students who feel a sense of emotional support and presence in online courses demonstrate higher levels of persistence and engagement. This underscores the value of designing platforms that can recognize and respond to learners' affective states.

Emotion Detection in Educational Contexts Using Deep Learning Technology

The evolution of AI technology, notably deep learning, facilitates automatic and accurate identification of students' emotions based on their facial expressions. This technology enables learning platforms to identify and interpret the emotional state of students in real time, thus making the learning journey more adaptive. According to Bagane et al., (2022) major emotions like happiness, sadness, anger, surprise, fear, disgust and neutral feature matches can be achieved by convolutional neural network (CNN) in up to 85% accuracy rate. In some cases, this could involve, for example, teachers and learning systems that will be able to track the emotional state of a student while learning, so as to give more adequate feedback.

A few of the studies also discuss the effectiveness of deep learning algorithms that have proved successful in warning emotions with highest accuracy. Anbananthan Pillai Munanday et al. (2023) showed that transfer learning-optimized CNNs improved detection accuracy in various lighting conditions and face viewing angles. This is especially true in online learning where the

conditions of video and expressions are different, and platforms like Videmo can offer people more accurate emotional feedback. Online learning can be greatly promoted by emotion detection deep learning technology. Furthermore, the inclusion of emotion detection and a video discussion feature would enable Videmo to assist lecturers in developing an understanding of the emotional needs of students, thereby allowing them to tailor teaching methods for a more inclusive and adaptive environment.

Although emotion detection systems have demonstrated some potential, performance could be affected by environmental factors such as lighting, camera angles, and visibility of participants faces (Bagane et al., 2022). These technical limitations should be considered in educational settings, and the results here must be understood as preliminary until confirmed by studies on larger, more diverse samples. Videmo must hence be regarded as an early-stage prototype and evaluated as such, in line with the suggestion of a neutral research position.

Methodology

This research uses a system development-based experimental approach. There are three stages, namely: 1) platform development, 2) technical testing, 3) implementation and user evaluation.

In the first stage, *the Videmo platform was developed* using PHP, JavaScript and the face-api.js library to detect faces, analyze emotions, and record discussion videos. The main tools, VBD and EDDL, were integrated to support online discussions with real-time emotion analysis.

The second stage involved *technical testing of the emotion detection model*. The models used are SSD MobileNet V1 for initial face detection, Tiny Face Detector for detailed facial feature detection, and Face Expression Model for detecting emotion classifications (happy, sad, angry, surprised, neutral, fear, and disgusted). The three models are then tested and evaluated using customized datasets with Precision, Recall, and F1-score metrics. Environmental factors such as lighting and camera angle were monitored but noted as potential variables influencing detection accuracy.

The third stage is *implementation and user evaluation*. The Videmo platform was implemented in an online discussion forum with 34 students and 2 lecturers. Participants were recruited through convenience sampling from two classes, and all provided informed consent prior to participation. There are two classes, namely class A guided by Lecturer 1 with 17 students and class B guided by Lecturer 2 with 17 students. Emotion data was collected from each student in each class A and B when conducting video-based discussions through the Videmo platform. In class A, the discussion was about light topics, namely “The benefits of group discussion in online learning” and “A pleasant online learning experience.” While in class B, they discussed complex topics such as “The effectiveness of online learning in building 21st century skills” and “Ethical challenges in the use of artificial intelligence for education.” Surveys were conducted to measure the level of user satisfaction and learning effectiveness. The emotional data obtained was then analyzed quantitatively to determine the pattern of students’ emotional engagement. This study was performed as a so-called controlled simulation in a non-course context to be able to focus on the platform functionality and user experience, an aspect

that must be taken into account when interpreting results. While the sample size was sufficient for this study, it represents a limitation in terms of generalizing the findings.

The diagrams below demonstrate Videmo's use case diagram and feature workflows to give a better insight into how the system works and how users interact with it. Here is the diagram which shows how different modules of the platform interact to provide real-time emotion detection and demonstrate video-based discussions.

Figure 2

Use Case Diagram

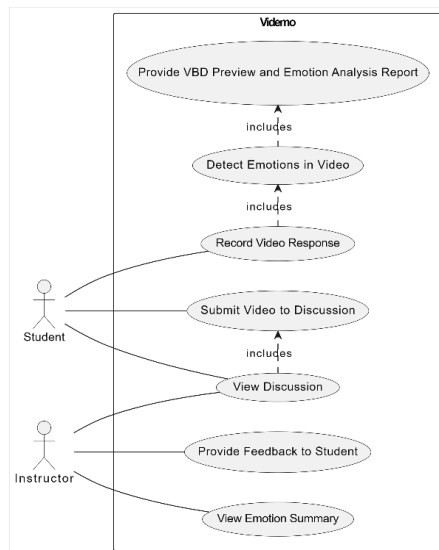
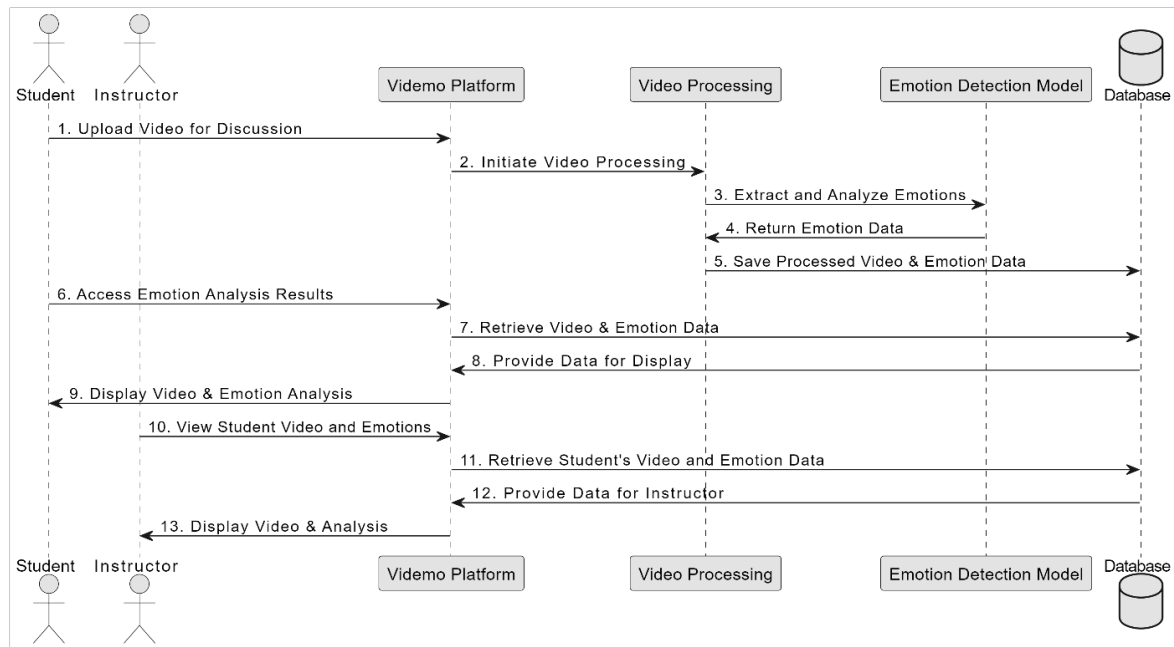


Figure 3*Feature Workflow Diagram*

Videmo utilizes various models and algorithms to support emotion analysis in video discussions:

a) SSD MobileNet V1

This model is used as an initial filter to detect faces in the video. With an efficient object detection algorithm, the MobileNet V1 SSD provides accurate face position estimation.

b) Tiny Face Detector

The model is optimized to detect facial features in detail, even under varying lighting conditions and face orientation. Tiny Face Detector ensures accuracy of detection, especially in non-ideal environments, while maintaining performance.

c) Face Expression Model

The model classifies facial expressions into seven major emotion categories (happy, sad, angry, surprised, neutral, fear, and disgust) using deep learning algorithms. The model has been tested and optimized to classify facial expressions with high accuracy.

All these models are integrated with the face-api.js library, which enables JavaScript-based analysis directly in the web environment.

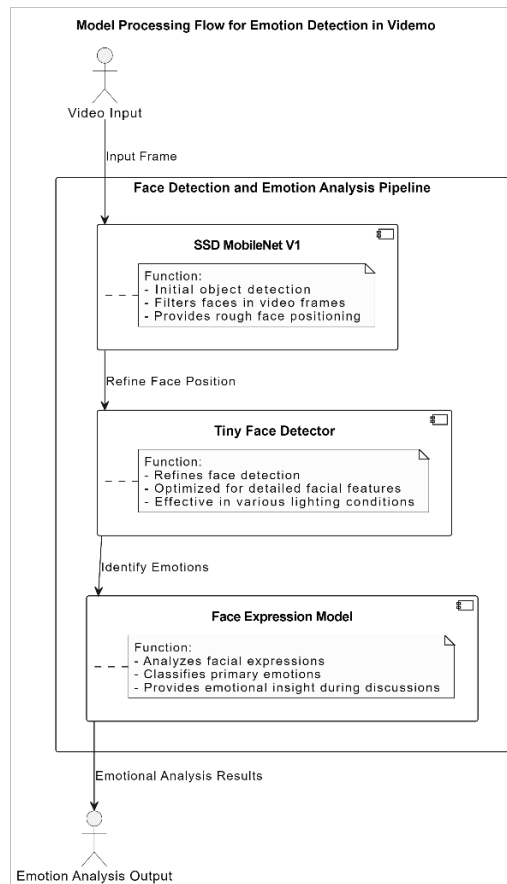
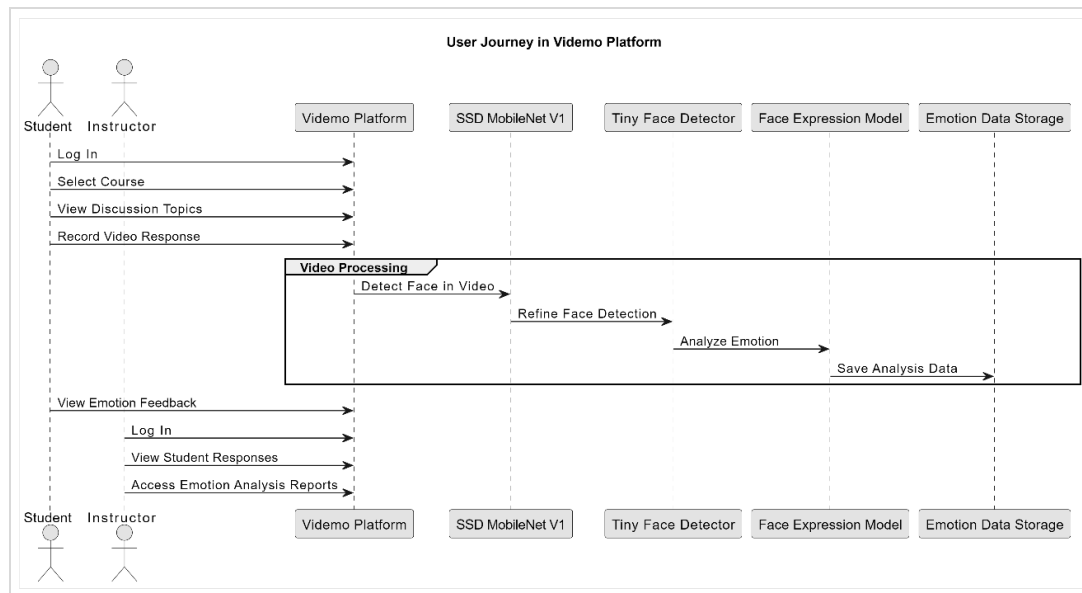
Figure 4*Model Processing Flow for Emotion Detection*

Figure 5*User Journey in Videmo Platform*

The Videmo development process consists of several key stages:

a) *Requirement Analysis*

The development of Videmo started with identifying the need for a platform that supports video-based discussions and provides emotion analysis. This approach was taken to enhance more in-depth and emotional learning interactions.

b) *Model Integration and Fine-Tuning*

Each model was integrated and matched with student recorded data to ensure the accuracy of emotion analysis. Model parameters were incrementally adjusted to optimize the accuracy of emotion detection and classification.

c) *User Testing and Feedback.*

At this stage, users participated in initial testing, providing feedback on the accuracy and relevance of the emotion analysis results. This feedback was used to make adjustments to the detection algorithm to make the analysis results more relevant to the learning context.

d) *Validation and Iteration.*

Validation is done by applying Videmo to real discussions to ensure the accuracy of the model under various conditions (light, face angle). Iterations were conducted to address shortcomings and ensure the system is able to provide consistent emotional analysis.

e) *Data Storage and Security Compliance.*

Videmo uses strict data storage and security policies, ensuring that every video and emotion analysis result is stored securely. Access rights are restricted to authorized parties to maintain student privacy.

These methodological choices restrict the generalizability of the findings, which are intended as preliminary and guiding evidence to design larger studies.

Result

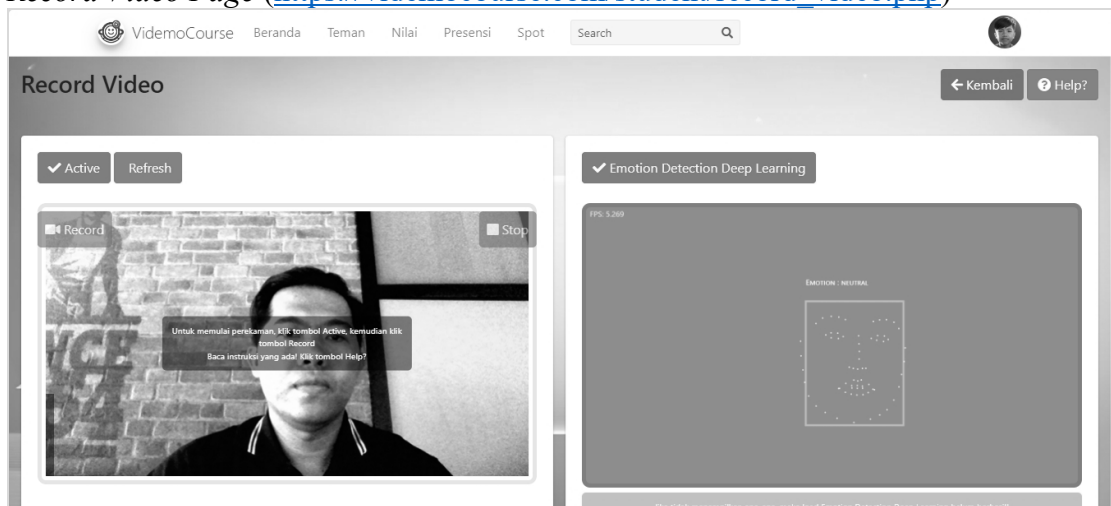
Description of Videmo Feature

Video-Based Discussions (VBD)

The VBD feature in Videmo provides a video-based discussion platform that allows students to record their discussion responses on video. VBD enables asynchronous interaction, allowing lecturers and students to engage in a more meaningful discussion than text-association. When students record video responses to the discussion on the Videmo platform, they are able to view real time emotion data which offers deep insights as to their emotional engagement during the recorded discussion.

Figure 6

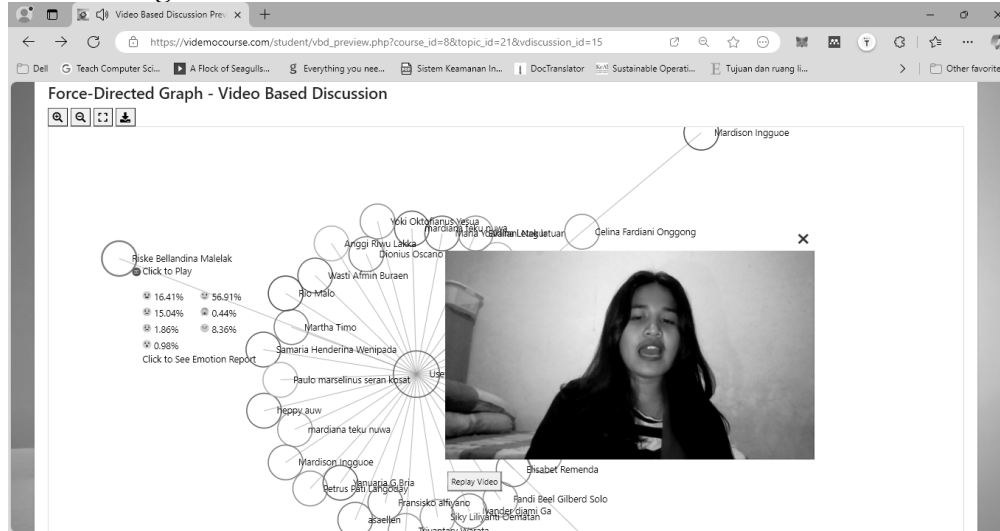
Record Video Page (https://videmocourse.com/student/record_video.php)



Emotion Detection Deep Learning (EDDL)

EDDL utilizes deep learning algorithms to automatically detect emotions from students' facial expressions in videos. It is built to identify seven basic emotional states: happiness, sadness, anger, surprise, neutrality, fear, and disgust. EDDL works in the same time the discussion video is being recorded, where the overall percentage of emotions calculated during the recording is stored on the database in addition to the discussion video information. The results of this emotion analysis are displayed on the VBD preview which can provide lecturers with information about the emotional dynamics that occur during online discussions.

Figure 7
Preview Page Video-Based Discussion



Technical Testing Results

Technical testing has been conducted before it was used in real online learning to see if the model used in Emotion Detection Deep Learning is working well. The technical tests conducted in the development of Videmo are as follows:

Accuracy and Reliability of Emotion Detection Model

The emotion detection model was tested under a range of conditions, including different lighting levels, facial angles, and types of emotional expressions. The technical test involved taking video samples from university students under varying lighting conditions and using three main models: SSD MobileNet V1 for initial face detection, Tiny Face Detector for detailed facial feature detection, and Face Expression Model for emotion classification. The accuracy and robustness data was tested using Precision, Recall, and F1-score metrics, which are standard in the evaluation of detection and classification models.

$$\text{Precision} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Positive (FP)}}$$

$$\text{Recall} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Negative (FN)}}$$

$$\text{F1 - Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Testing included 34 student video samples selected thematically by lighting, facial angles, and emotional expressions. The dataset has been labelled with ground truth in the form of bounding boxes for face detection and emotion categories for classification. Face detection in the video is achieved using the MobileNetV1 SSD model. Intersection over Union (IoU) use to compare the bounding box of model detection results and the ground truth bounding box for evaluation. Detection is considered correct if $\text{IoU} > 0.5$ (True Positive). If there is no face but the model detects, it is a False Positive, where as if there is a face but is not considered by the model, it is a False Negative. Tiny Face Detector is a tool that finds facial features more specifically and

under adverse environmental situations, like not very bright light or face alignment. The bounding box model results are compared with the ground truth using the same method as MobileNet V1 SSD Model. For the Face Expression Model, performance was evaluated based on emotion classification accuracy rather than bounding box detection or IoU. The Face Expression Model is responsible for classifying facial expressions. We quantitatively compare the emotion hypothesis predictions given by the model with the ground truth labels. Therefore, the evaluation did not involve bounding boxes or IoU; instead, it measured the proportion of predictions that matched the ground-truth labels. The accuracy of each model test is summarized in Table 1:

Table 1

Face and Emotion Detection Model Accuracy

Model	Precision (%)	Recall (%)	F1-score (%)
SSD MobileNet V1	94.8	95.2	95
Tiny Face Detector	91.3	92.8	92
Face Expression Model	88.1	87.9	88

From the table, it can be seen that SSD MobileNet V1 out of all achieves a better accuracy with the F1-score of 95.0%, and this is followed by Tiny Face Detector with an F1-score of 92.0% and Face Expression Model with an F1-score of 88.0%. From these results, we can conclude that combining these three models we can detect faces and emotional expressions in less-than-optimal environments.

Evaluation of System Robustness to Lighting and Angle Variations

Additional tests were carried out to assess the system's robustness across various lighting conditions and face viewing angles. These experiments involved adjusting lighting intensity (low, medium, and high) and face orientation (facing the camera at 0°, as well as at 30° and 45° angles from the camera). Each condition was tested with 34 samples to assess the stability of the system. Each sample is analyzed by the MobileNet V1 SSD model and Tiny Face Detector, resulting in a prediction bounding box. This bounding box is compared to the ground truth bounding box using Intersection over Union (IoU), with detection considered true positive if IoU > 0.5. Accuracy was calculated for each combination using the formula:

$$\text{Accuracy} = \frac{\text{Number of Correct Detections (True Positives)}}{\text{Total Number of Faces in Ground Truth}} \times 100\%$$

The test results are shown in Table 2.

Table 2

Effect of Lighting Conditions and Viewing Angle on Face Detection Accuracy

Condition – Angles From the Camera	Low Lighting (%)	Medium Lighting (%)	High Lighting (%)
Angles 0°	91.2	95.3	96.8
Angles 30°	88.4	93.7	95.1
Angles 45°	82.7	89.5	91.4

Description:

- a. Low Lighting: Dim or minimal light
- b. Medium Lighting: Standard light (normal lighting)
- c. High Lighting: Bright or excellent light
- d. 0°: The face is directly facing the camera
- e. 30°: The face is tilted by 30°
- f. 45°: The face is tilted more sharply by 45°.

The results demonstrate that the high illumination with a viewing angle of 0° detects the optimally good-face accuracy of 96.8%. At low illumination, the accuracy was as low as 82.7% when the angle was 45°, which suggest that it is more difficult to detect the face when the illumination is less and the face angle is sharper. But, the results were still around 80% accuracy in all situations, which tells the high stability of the MobileNet V1 SSD with Tiny Face Detector combination going through different situations.

Evaluation of Face Expression Models for Emotion Classification

Face Expression model-testing on seven core emotions or facial expressions to determine how accurate results are for predicting emotions alone. The prediction accuracy of the model was obtained for each emotion using 34 samples. The model will output the emotion for every sample. Testing compares the model prediction with ground truth. If the predicted value in the model differs from the ground truth, it is false. If it is the same then it is correct (Correct Prediction). Accuracy is calculated for each emotion based on the percentage of correct predictions against the total samples of that emotion. The accuracy formula used:

$$\text{Accuracy} = \frac{\text{Number of Correct Prediction}}{\text{Total Number of Samples}} \times 100\%$$

The characteristics for recognizing facial expressions include the mouth, eyes, and eyebrows. Happy expressions are characterized by a smile, raised lip corners, and narrowed eyes due to raised cheeks. Sad expressions are characterized by lowered lips, raised inner eyebrows, and eyes that appear haggard. Angry is characterized by downward furrowed eyebrows, narrowed eyes, and compressed or tightly pursed lips. Surprised shows a wide open mouth, raised eyebrows, and dilated eyes. Neutral is characterized by a relaxed face with no particular

expression. Fear is characterized by eyes wide open, eyebrows raised to the center, and mouth slightly open or pulled back. Disgust is characterized by pursed lips, raised nose, and narrowed eyes, indicating discomfort or disgust.

The results of this emotion accuracy test are shown in Table 3.

Table 3

Prediction Accuracy of Face Expression Model Based on Emotion

Emotion	Prediction Accuracy (%)
Happy	91.2
Sad	85.5
Angry	84.9
Surprised	89.3
Neutral	92.1
Fear	80.7
Disgusted	82.5

The table shows that the highest accuracy was reached for the emotions “Neutral” (92.1%) and “Happy” (91.2%), while the lowest accuracy was recorded for “Fear” (80.7%). This variation may be attributed to the complexity of facial expressions associated with certain emotions, like “Fear” and “Disgust.”

User Testing Results

User Satisfaction Level

User testing involved 34 students and 2 lecturers to evaluate the VBD and EDDL features on the Videmo Platform. Testing was conducted in three stages: (1) participants engaged on the platform with two types of discussion topics, namely light topics such as “The benefits of group discussion in online learning” and “An enjoyable online learning experience,” as well as complex topics such as “The effectiveness of online learning in building 21st century skills” and “Ethical challenges in the use of artificial intelligence for education,” (2) emotion data from discussions were recorded using the EDDL feature and analyzed based on emotion categories, and (3) participants filled out a satisfaction survey to evaluate the ease of use of the platform and the benefits of the emotion feature in discussions.

Table 4

Survey Results for Students

No.	Survey Question	Agree	Disagree	Percentage Agree (%)
1	Did the VBD and EDDL features help you engage more actively in the discussion?	30	4	88.24%
2	Do you feel comfortable using the VBD and EDDL features?	29	5	85.29%
3	Did the VBD and EDDL features improve your understanding of the discussion material?	28	6	82.35%

4	Do the VBD and EDDL features make it easier for you to express your opinions?	31	3	91.18%
5	Did the VBD and EDDL features help you co-operate with other participants?	29	5	85.29%
6	Did the VBD and EDDL features help you keep your focus during the discussion?	27	7	79.41%
7	Does the emotion data from VBD affect the way you interact?	28	6	82.35%
8	Are VBD discussions more efficient than regular discussions?	30	4	88.24%
9	Do the VBD and EDDL features increase your confidence in speaking?	28	6	82.35%
10	Do the VBD and EDDL features motivate you to be more active in discussions?	29	5	85.29%
11	Did the VBD and EDDL features help you understand other participants' perspectives?	31	3	91.18%
12	Do you feel that the VBD and EDDL features improve the quality of discussions?	30	4	88.24%
13	Do the VBD and EDDL features make discussions more enjoyable?	28	6	82.35%
14	Is the VBD and EDDL interface of Videmo Platform easy to use?	32	2	94.12%
15	Do VBD and EDDL features make online learning more engaging?	30	4	88.24%
Total		440	70	86.27%

The survey showed that the majority of students felt that Video-Based Discussion (VBD) and Emotion Detection Deep Learning (EDDL) feature in Videmo Platform had a positive impact on their engagement in online discussions. A total of 86.27% of students expressed satisfaction with the various features offered by this platform. There are several important points that emerged from this survey:

a. *Improving the quality of discussion*

Total 91.18% of students felt that VBD and EDDL feature, helped them better understand their peers' points of view. Not only that, but the online discussions were also more enjoyable and richer because students could express their opinions in a more expressive way. Overall, they also felt that the quality of the discussion improved.

b. *Making it easier to express opinions*

The VBD feature, according to 91.18% of respondents, made it very easy for them to convey their ideas. Compared to text-based discussions, they felt that videos allowed emotions and body language to be better conveyed. VBD and EDDL feature in the Videmo platform helped them feel more confident in discussions.

c. *Ease of user interface*

Total 94.12% of students agreed that Videmo's interface was very easy to use. The platform is intuitively designed, so it does not take long for students to understand how it works. They even felt comfortable when accessing the available features.

d. *The emotion data effect for students in video-based discussion.*

Item 7 student survey question: “Does the emotion data from VBD affect the way you interact?” Responses revealed a various answers or perceptions. Total 82.35% of students agreed that emotion data affected their interaction, follow-up interviews highlighted mixed perceptions. Some students stated that knowing their emotions were being analyzed encouraged them to engage more seriously and reflectively in online discussions. Others, however, admitted feeling mildly self-conscious, particularly in expressing negative emotions or controversial views. These varied responses suggest that while emotion data may positively increase awareness and reflection, it could also introduce a sense of performance pressure.

From the results of this survey, it appears that students feel more free and comfortable when sharing ideas through video. They also felt that the emotional expressions and body language captured in the online discussion helped to create a more interactive atmosphere and supported deeper engagement.

Table 5

Survey Results for Lecturers

No.	Survey Question	Agree	Disagree	Percentage Agree (%)
1	Does the emotion data generated by the Videmo platform make it easier for you to understand student engagement?	2	0	100.0%
2	Does the emotion data generated by the Videmo platform provide new insights into student responses?	2	0	100.0%
3	Does the emotion data generated by the Videmo platform help you identify struggling students?	1	1	50.0%
4	Does the emotion data generated by the Videmo platform help you plan learning interventions?	1	1	50.0%
5	Is the emotion data generated by the Videmo platform relevant for learning evaluation?	2	0	100.0%
6	Does the emotion data generated by the Videmo Platform improve the quality of student discussions?	1	1	50.0%
7	Does the emotion data generated by the Videmo platform make it easy for you to provide feedback?	2	0	100.0%
8	Do you find the emotion data generated by the Videmo platform helpful in understanding group responses?	1	1	50.0%
9	Does the emotion data generated by the Videmo platform support decision-making in learning?	2	0	100.0%
10	Does the emotion data generated by the Videmo platform enhance your online teaching experience?	1	1	50.0%
Total		15	5	75.0%

A total of 75% of lecturers' statements expressed that the EDDL feature helped them to better understand how students engage in online discussions. The emotion data generated through this feature allows lecturers to be more sensitive to students' emotions in online discussions. It also helps lecturers to provide feedback that feels more relevant and personalized.

However, there is an important caveat. For the question of whether this emotion data can help lecturers in developing learning interventions, only 50% agreed. This result, in fact, signals that while this feature is quite useful, its use may not be optimal as it requires a deeper understanding of how emotion data can be applied directly in learning strategies.

In addition, this study itself still has limitations that need to be recognized. This study only involved two lecturers, and did not actually test the Videmo platform in real course learning. On the contrary, the online discussion conducted in this study was only a simulation, focusing on two types of topics: light and complex. Therefore, the findings obtained are more representative of the initial potential of Videmo's features, and cannot be used as a complete picture of how this platform works in real learning situations. As such, the results of this study are promising, but wider implementation in real learning contexts is needed to test and validate its potential.

Analysis of Engagement and Learning Effectiveness

The test was conducted on two classes, each consisting of 17 students, with the division based on the lecturer and the type of discussion topic. Class A (17 students), supervised by Lecturer 1, discussed light topics. Meanwhile, class B (17 students), supervised by Lecturer 2, discussed complex topics. In class A, the emotion data showed the dominance emotions is “happy” (40%) and “neutral” (35%) emotions. The emotion data detected in class A reflected a sense of comfort and good understanding of the discussion material. In class B, the dominating emotions were “fear” (31%) and “surprise” (30%) emotions. This result shows that in class B there is a cognitive challenge and curiosity of students towards more difficult material.

Table 6

Students' Emotion Distribution on Light Topics and Complex Topics

Emotions	Mean of Light Topic 1	Mean of Light Topic 2	Mean of Light Topic	Mean of Complex Topics 1	Mean of Complex Topics 2	Mean of Complex Topic
Happy	42%	38%	40%	20%	18%	19%
Sad	8%	6%	7%	12%	10%	11%
Angry	5%	7%	6%	14%	16%	15%
Surprised	12%	16%	14%	28%	32%	30%
Neutral	34%	36%	35%	22%	18%	20%
Fear	10%	12%	11%	30%	32%	31%
Disgusted	3%	5%	4%	8%	6%	7%

The emotion data generated from EDDL provides a clearer picture of the level of student engagement in the discussion. From the analysis of the video-based discussions, it was found that “happy” and “neutral” emotions dominated student responses on light topics, while on complex

or critical topics, “fear” and “surprise” emotions were more common. This suggests that emotional engagement is in line with students' level of understanding of the discussion material.

The dominance of “happy” and “neutral” emotions on light topics reflects a supportive discussion environment and provides a sense of comfort for students. Meanwhile the high emotions of “fear” and “surprise” on complex topics show the cognitive challenges students face in understanding more difficult discussion topics, and also trigger curiosity. Emotions on complex topics indicate the need for support strategies, such as scaffolding or additional clarification, to help students overcome challenges.

These results reveal the preliminary evidence for that Videmo's VBD and EDDL features supported student engagement and may provide instructors with useful emotional insights, but needs further validation in the settings of real courses.

Discussion

Relevance and Effectiveness of Video-Based Discussion (VBD) in Online Learning

The study of this feature shows an impact on the student experience in Videmo via the Video-Based Discussion (VBD) method. The majority of students perceived that video-based discussions enabled them to interact on a deeper level than text-based discussions. With video, they can express emotions and body language that get lost in plain text.

Research by Milovic and Dingus (2021) supports this finding, where video-based discussions were used to mitigate the feelings of isolation that are common with online learning. Relatedly, the Community of Inquiry (CoI) model presented by Garrison et al. (1999), highlights the importance of social presence in creating meaningful learning experiences. In this case, Videmo helps students to feel more emotionally connected in the online learning environment.

There are some additional interesting aspects on the lecturer's perspective, that the VBD feature provides additional benefits. Due to the recording of students' facial expressions and body language, lecturers can better determine whether or not students actually comprehend with what they are teaching. The survey showed that 91.18% of students felt that VBD helped students to state their opinion more effectively, while 94.12% felt that Videmo's interface was easy to use. This shows that overall, VBD not only enhances the quality of discussions, but also provides a supportive environment for collaborative learning. It is at the same time supporting Media Richness Theory (Daft & Lengel, 1986), which argues that video provides a richer medium for exchanging complex information compared to text. Additionally, according to Social Information Processing Theory (Walther, 1992), being able to see the facial expression and hear the tone of voice of peers can aid in developing interpersonal relationships even through a computer-mediated environments.

Emotion Detection to Support Learning Evaluation

The Emotion Detection Deep Learning (EDDL) feature in Videmo makes an important contribution in measuring students' emotional engagement, which is often an indicator of learning comprehension and motivation. The EDDL feature in Videmo has been shown to accurately detect seven discrete emotions (happiness, sadness, anger, surprise, neutrality, fear, and disgust) with a high degree of accuracy. Particularly the emotions “neutral” (92.1%) and “happy” (91.2%), while the lowest accuracy was recorded for “fear” (80.7%). This capability

enables lecturers to understand how topics resonate with students emotionally, thus informing more tailored and meaningful feedback.

In the survey, 75% of lecturers responded that the emotion data helps them to understand student engagement better. For example, the dominant emotions of “fear” and “surprise” on complex topics indicate the cognitive challenges students’ experience. This aligns with the theory of Pekrun (2006), which theorizes that joy is a positive emotion that relates to an increase in motivation to learn, whereas fear is an emotion describing the need for further intervention or support. These results also resonate with findings from Jiang and Koo (2020), who reported that fostering emotional presence in online courses strengthens community and engagement. By making emotions visible, Videmo supports timely scaffolding, which is consistent with Control-Value Theory’s emphasis on regulation of achievement emotions. Teachers also can provide students with more personalized support by understanding their emotional states, which enhances the overall learning process. This functionality allows lecturers to give feedback not only on the content but also to consider emotional issues, which leads to a more comprehensive evaluation.

However, we should exercise caution regarding the interpretation of certain emotions like “fear” or “disgust.” These feelings don’t always relate directly to what’s being learned and may be impacted by external forces: environmental conditions, the students’ mood throughout the discussion, etc. Thus, even if this feature has potential, its use must be further refined in a more realistic and matched way with emotion data.

Advantages of Videmo Compared to Other Platforms

This unique combination of VBD and EDDL offers potential benefits over many existing platforms. Besides offering a video-based discussion area, Videmo also provides lecturers with emotional insights that they can use to adapt their approach to the learning environment. For instance, when emotions like “confusion” or “frustration” are detected, the lecturers can immediately explain additional details to prevent students from losing understanding about the material. This advantage is reinforced by the overall student satisfaction rate of 86.27%, with 91.18% feeling that VBD improved the quality of discussions. This implies Videmo is not just a communication tool for online learning platform, but also a more comprehensive human assessment tool. Utilizing the content and emotion data, Videmo creates a more experimental style of learning for the student on an online learning platform. However, as noted by Redmond et al. (2023), engagement strategies should be verified empirically for different contexts; accordingly, the benefits of Videmo need to be demonstrated in longitudinal studies before we can generalize its effect or impact.

Although Moodle, being one of the most popular learning management systems (LMS) available today, already includes the features to create discussion forums and some basic interactive resources, these tools are text-based for the majority and do not offer native emotion analysis or video-based discussion integration. Therefore, Moodle forums may fail to capture students’ emotional expressions, which are relevant in order to understand engagement and social presence. Videmo does not rather replace Moodle, but provides an additional emotional layer of interaction with a video-based discussions and real-time emotion detection capabilities. In this way teachers can not only assess the cognitive value of what students contribute, but also follow their emotional engagement. The future addition of Videmo into other LMS systems, such as Moodle or as a plug-in or an external activity, could result in a more complete solution where

both the robust course management capabilities from other LMS and the emotion detection feature of Videmo is offered.

Technical Limitations and Challenges

Videmo platforms do have a lot of potential, but there are certainly some technical limitations to take into account. One of the problems discovered is that the detection sensor for emotions fails when lighting conditions are poor and/or the student's face is not turned towards to the camera. For example, from the tests conducted, the face detection accuracy reached 96.8% in bright lighting, but decreased to 82.7% in low lighting. Such conditions are a clear challenge, particularly in online learning, where users' conditions of the environment can differ radically. In addition, the interpretation of certain emotions, such as "fear" or "disgust," can sometimes be confusing. These emotions may not always be directly related to the topic of discussion, but can be influenced by other factors, such as the student's mood or distractions from the surrounding environment. Therefore, it is important for developers need to ensure that these emotion detections are both accurate and relevant with respect of the educational context, to avoid introducing bias on their usage.

This study was performed on a relatively small scale. The discussions tested were still simulations, not real learning situations. The study only involved 34 students and 2 lecturers, and focused on two types of discussion topics, namely light topics and complex topics. This is so small scale that the observed results represent more the initial potential of Videmo rather than the real impact in daily exploitation. Future studies involving larger, more diverse samples and controlled comparisons across instructional contexts are necessary to validate and extend these initial findings.

This limitation opens up a possible area of future research. Future studies may recruit larger samples in real learning environments. These might focus on testing across different environmental settings such as lighting and hardware to increase validity and efficacy across different contexts. Taken together, these limitations suggest that the current results must be considered as preliminary evidence and not definitive conclusions. This work represents the first phase of our research which will continue with a quasi-experimental design with control and experimental groups to go deeper in the investigation about the affirmative impact on teaching a course by means of Videmo.

Future Implications and Recommendations

Future development of Videmo should focus on improving the technical reliability of emotion detection, expanding validation in authentic course settings, and preparing instructors to interpret emotion data pedagogically. Similar to the suggestions of Martin and Bolliger (2018), future research should consider the role of such tools in supporting learner autonomy, faculty presence, and cognitive engagement across diverse online learning environments. To make Videmo a more reliable and educationally meaningful tool for online learning, several important steps can be taken:

a. Improve the Accuracy of the Technology

In this study, one of the biggest challenges was the decrease in emotion detection accuracy in low lighting conditions or when students' faces were not fully visible. This is a very common occurrence in online learning, where the user's environmental conditions are often difficult to control. By utilizing techniques such as transfer learning or more advanced deep learning models, Videmo can be more adaptive to

these conditions. This will certainly strengthen its reliability in various learning situations.

b. Integration of NLP-based Sentiment Analysis

The future research is to develop a sentiment analysis based on Natural Language Processing (NLP). This feature enables deep analysis of students' verbal responses that can be analyzed to understand their emotions more deeply. By merging emotion data from video and text, it can provide lecturers with a much more holistic view. However, this would surely enhance the learning assessment mechanism.

c. Improved Validation with a Broader Study

Given that this was a small-sample study, the next step will be to conduct a larger scale study. Testing Videmo with real courses, and bigger numbers of students, will give a more accurate picture of how the system functions in the wild. Future studies should also examine whether Videmo aligns with learners' needs, instructional goals, and authentic online course practices.

d. Training for Lecturers

Educational technologies such as Videmo are effective only when instructors understand how to use them appropriately. As would training on using Videmo platform, and reading emotion data from the platform. This training not only must include how to identify emotion data but also how to connect that data with learning strategies to enhance activity relevance to student needs.

Ethical Considerations and Privacy

The integration of video-based discussion and emotion detection in Videmo raises important concerns regarding user privacy, ethical data use, and psychological comfort. Although Videmo collects emotional data strictly for educational research purposes, the recording of students' videos and the analysis of emotional data may still lead to discomfort or self-consciousness. To address these concerns, all participants were informed in advance about how their videos and emotional data would be used, and only those who provided consent were eligible to participate in this study. Data storage in Videmo follows strict access and encryption protocols, and emotional data are not used for purposes beyond this research.

Conclusion

Through the development of our Videmo platform which integrates VBD and EDDL technologies, we present a new option for online learning with a more in-depth and meaningful approach. Students are able to use the VBD feature to express feelings and emotions and body language which are not normally expressed in text-based discussions, improving their social presence in the online learning environment. EDDL technology enables lecturers to gain insight into students' emotional responses to topics of discussion, offering a more comprehensive view of student engagement. The survey results indicate that Videmo has been successful in improving user engagement and satisfaction as 86.2% of students stated that they have participated more often in discussions and 75% of lecturers agreed on finding it easier to understand student responses with Videmo. Technical tests also showed a high level of emotion detection accuracy, especially for "happy" and "neutral" emotions, despite challenges in certain

lighting conditions and viewing angles. While the platform still faces some technical challenges, particularly in less-than-ideal video conditions, further development of the emotion detection technology and integration of Natural Language Processing (NLP)-based sentiment analysis could improve the reliability of the system. This study adds to a growing literature on online learning by combining emotion analytics with video-based discussion and provides empirical support that emotional presence can be predictably measured and used for adaptive instruction. Next steps are to introduce a quasi-experimental design, including control and intervention conditions in actual course contexts, in order to rigorously test the impact of Videmo on engagement, learning achievement, and emotional regulation over time.

Declarations

Acknowledgment

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Ethics Approval and Consent to Participate

This study was approved by the Research Ethics Committee of Universitas Citra Bangsa (No: A.0221/SU/FKIP/UCB/VIII/2024). All participants provided written informed consent prior to data collection, and all procedures were conducted in accordance with institutional ethical standards for research involving human subjects.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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Listening to Adjunct Faculty Voices: A Case Study for Supporting Adjunct Faculty Across Career Stages at a Small Community College

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Abstract

Community college adjunct faculty, who teach a majority of first-year courses, face varied challenges related to limited access to ongoing support. This qualitative study examined the effects of an instructional coaching program on community college adjunct faculty's self-efficacy and ability to enhance instructor presence in online courses. Using a multiple case study research design, we investigated the impact of an instructional coaching program on two early-career (<7 years) and two mid- to late-career (>12 years) online adjunct faculty. Self-Efficacy Theory (Bandura 1997, 2005), the Community of Inquiry model (Garrison 2016a), and Richardson et al.'s (2015) operationalization of instructor presence provided the interpretive frameworks for analyzing coaching session data and faculty-student interactions recorded in pre- and post-intervention archived courses. Findings revealed self-efficacy gains across career stages, with early-career faculty demonstrating a stronger willingness to adopt new technologies such as GenAI, resulting in significant improvements in their self-efficacy and application of newly acquired skills. Mid- to late-career faculty expressed higher perceived confidence from their extensive face-to-face teaching experience, with a more cautious and thoughtful approach to implementing new teaching strategies in their course. These results suggest that when ongoing professional development is designed to meet the unique needs of adjunct faculty across different career stages, it can improve their sense of institutional belonging and retention.

Keywords: Adjunct faculty, instructional coaching, community college, instructor presence, regular and substantive interaction, faculty development

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Adjunct or “part-time” faculty at community colleges often face unquestionably challenging, and at times dehumanizing conditions, characterized by minimal institutional support and limited access to faculty development. Recent studies consistently show that adjuncts lack job security, and they are routinely excluded from institutional decision-making and professional development (American Association of University Professors, 2021; Potts, 2021; Tanenbaum, 2024). As a result, they often feel isolated, underprepared, and left out of university conversations (Childress, 2019; Reichman, 2021). Additionally, the lack of structured professional development contributes to decreased faculty engagement and integration, negatively impacting student retention and success (Thirolf, 2016). Despite these circumstances, adjunct faculty represent one of the fastest-growing job sectors in higher education and play a vital role in teaching introductory courses to academically underprepared students (Childress, 2019).

Parallel to the growth in adjunct faculty employment, online course enrollment has also expanded significantly. In 2019, 28.1% of students took some online courses, and 44.7% were enrolled exclusively online (NCES, 2020). While online learning is critical to the long-term success of higher education institutions (Brown et al., 2020), research shows that students in online courses, particularly at community colleges, often perform worse than their face-to-face peers (Xu & Jaggars, 2013, 2014). However, when instructors design inclusive, student-centered online courses, students can perform as well as or better than in face-to-face settings (Garman & Good, 2012). Faculty development that empowers instructors to enhance their instructor presence and foster an active learning environment is essential for bridging this performance gap. Closing these performance gaps calls for targeted faculty development, particularly for adjunct instructors, who frequently face unique barriers and lack access to necessary resources and training.

A recent survey by the Online Learning Consortium (OLC), in collaboration with WICHE Cooperative for Educational Technologies (WCET) and Every Learner Everywhere, noted widespread gaps in resources and support for adjunct faculty, particularly at small institutions where limited personnel complicates faculty development efforts (Davis et al., 2022). Building on these findings, the Supporting Online Adjunct Faculty Playbook offers actionable strategies for preparing and supporting online adjunct faculty (Weber et al., 2022). Inspired by these resources, this qualitative case study explored how innovative approaches could help a small community college in the American Southwest to enhance support for online adjunct faculty across different career stages.

This study explored online adjunct faculty experiences at Southwest Community College (SWCC, a pseudonym). Despite extensive research documenting adjunct faculty barriers, challenges, and faculty development needs, research about the effectiveness of instructional coaching in shaping online teaching practices is scarce (Butter & Gann, 2022). In an effort to work toward closing this gap, we explored how a facilitated asynchronous online training program combined with three follow-up instructional coaching sessions influenced adjunct faculty’s self-efficacy and ability to create meaningful student interactions through instructor presence.

Literature Review

Adjunct Faculty Challenges in Higher Education

Due to a lack of job security, adjunct faculty face difficult and precarious working conditions, often resembling those of gig employees (Tolley, 2018). Despite often teaching a similar course load as tenured faculty, adjunct faculty members are typically hired on a contract basis without access to healthcare, retirement plans, or paid time off (AAUP, 2018). This financial instability and lack of benefits take a toll on an adjunct faculty member's well-being and quality of life. Moreover, their limited access to institutional resources frequently hinders opportunities to develop meaningful relationships with their students and colleagues, contributing to a sense of isolation and disconnection (Childress, 2019; Potts, 2021; Thirolf, 2017).

The lack of institutional investment in adjunct faculty professional growth further exacerbates these issues. Unlike tenure-track faculty, who benefit from robust support and resources, adjunct faculty rarely receive additional institutional support (AAUP, 2018; Kezar & Maxey, 2013), particularly “for anything that costs money and is not related to preparing and delivering discrete course materials” (Coalition on the Academic Workforce, 2012, p. 13). These challenges are more pronounced for online adjunct faculty, particularly when it comes to equitable access to technology, institutional resources, and course preparation time (Center for Community College Engagement, 2014). Without faculty development focused on how to achieve deep and meaningful learning in the online classroom, they often make poor pedagogical choices, resulting in inconsistent learning outcomes and disengaged students (Bourdeaux & Schoenack, 2016).

To address these unique challenges, Self-Efficacy Theory (SET) offers a useful framework for exploring teacher readiness to teach online, emphasizing the personal beliefs and experiences that shape an instructor's sense of confidence. According to Bandura (1997), self-efficacy is shaped by four key factors: mastery experiences, vicarious experiences, social persuasion, and physiological feedback. For example, successfully implementing a new pedagogical strategy in an online course (mastery experience) has the greatest impact on self-efficacy. Observing skilled colleagues (vicarious experiences) offers instructors a way to visualize success in their own classrooms, whereas encouragement received by peers, students, or instructional coaches (social persuasion), reinforces the instructor's motivation and confidence to tackle difficult challenges. Finally, reduced anxiety when navigating a learning management system (physiological feedback) helps instructors feel at ease and more prepared to teach online. Together, these factors form the basis for understanding how instructors build confidence in online teaching.

Several studies demonstrate a high positive correlation between high levels of self-efficacy, a positive instructor mindset toward online teaching, high teacher and student ratings of instructional quality, reduced instructor anxiety, and improved student learning outcomes (Holzberger et al., 2013; Horvitz et al., 2014; Lee & Tsai, 2010; Liu et al., 2007). To tap into these benefits, institutions can design faculty development programs that focus on building mastery, facilitating observational learning, offering supportive feedback, and addressing instructors' emotional well-being. Building on Bandura's work, this study introduced an adjunct

faculty development program that combines asynchronous training with follow-up instructional coaching to enhance adjunct faculty self-efficacy for online instruction.

Faculty Readiness for Regular and Substantive Interaction (RSI) in Online Instruction

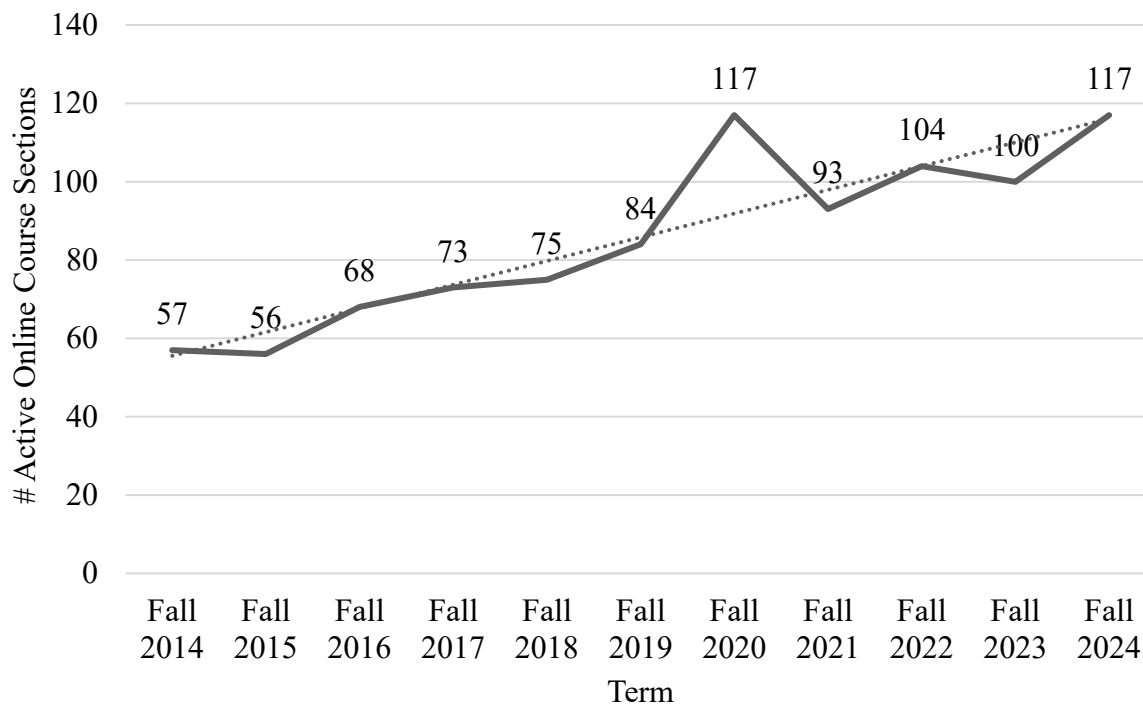
The rapid transition to online learning during the COVID-19 pandemic introduced another layer of complexity to the well-documented challenges of adjunct faculty at community colleges. In spring 2020, schools across the United States shifted instruction to online platforms to keep faculty and students safe, a process commonly referred to as Emergency Remote Teaching (ERT) (Hodges et al., 2020). Instructional designers and educational researchers made this distinction to ensure that hastily implemented remote instruction was not conflated with high-quality, intentional online course design. In doing so, they hoped to avoid the stigmatization of online learning as a lower-quality option based on these emergency responses. This rapid transition led to innovations in teaching modalities but also politicized the discourse around online learning, as stakeholders debated its effectiveness compared to traditional in-person instruction (Hodges et al., 2020).

In response to these developments, the U.S. Department of Education (ED) revised its definition of distance education, emphasizing the importance of regular and substantive (RSI) interaction between instructors and students as a fundamental measure of high-quality online instruction (34 CFR 600.2). The revised regulations require institutions to provide evidence that faculty engage meaningfully with students by providing direct instruction and individualized feedback, facilitating discussions, and often meeting with students in real-time. Setting them apart from self-paced correspondence courses, institutions need to demonstrate how distance education courses offer structured, regular opportunities for students to engage with their instructors (U.S. Department of Education, 2024). These guidelines help to ensure students receive a quality education that meets Title IV financial aid requirements, positioning RSI as an essential institutional benchmark of online course quality (Toppo, 2018; WCET & SAN, 2023). Responding to these developments, institutions need well-prepared instructors who can effectively apply online pedagogy that meets RSI requirements.

Growing enrollment in online courses reinforces the importance of preparing faculty to engage in effective online teaching practices. Between 2012 and 2021, distance education courses in the United States grew from 26.1% to 37.3% (Brown et al., 2020; National Center for Educational Statistics, 2022). For example, SWCC has witnessed a 26% enrollment decline over the last decade. Meanwhile, SWCC online course offerings increased by 105.3%, likely due to declining face-to-face enrollments (see Figure 1). This shift demonstrates the importance of distance education for institutional survival, but it also comes with its own set of difficulties. In particular, community college students tend to have lower pass rates (60.4% vs. 70.6%) in online courses compared to their face-to-face counterparts, with SWCC mirroring national trends (62.4% vs. 68.9%; Xu & Jaggars, 2013, 2014).

Figure 1

Frequency of Active Online Course Sections by Term at SWCC



Community of Inquiry and Instructor Presence

To address these performance gaps, instructors need opportunities to learn how to create inclusive, student-centered online courses. Professional learning should address the new RSI requirements and incorporate humanizing strategies that promote empathy, instructor presence, and community to boost student retention and success. Building on these insights, the current study investigated how a structured faculty development program that focused on developing self-efficacy for enhancing instructor presence helped instructors meet RSI guidelines and enhanced their readiness to teach online.

Research focused on online faculty learning have frequently drawn on both the Community of Inquiry (CoI) Framework and Self-Efficacy Theory (SET) to explore the development of self-efficacy in online teaching (Bandura 1997, 2012; Garrison, 2016a; Garrison, 2016b; Robinia & Anderson, 2010). According to the CoI framework, to “achieve deep and meaningful learning,” instruction needs to occur in “a collaborative community of inquiry” (Cleveland-Innes et al., 2019, p. 67; Garrison, 2016b). Born out of two decades of empirical research, deep and meaningful learning stems from “the development of three interdependent elements: (a) social presence, (b) cognitive presence, and (c) teaching presence” (Cleveland-Innes et al., 2019, p. 68). An online course design fosters social presence by encouraging students to express their identities through open communication, trust, and group cohesion. Cognitive presence engages students to think deeply and critically about the course content

through reflection and collaboration. Teaching presence refers to the instructional design, facilitation, and direct instruction required to achieve meaningful learning (Garrison, 2016a; Garrison, 2016b). When all the right conditions are in place, these elements enhance student learning, making them essential for online course design.

Grounded in the CoI framework, instructor presence combines both social and teaching presence during a live online course (Richardson et al., 2015). It refers to the actions and behaviors related to authentic engagement between instructor and students (Richardson et al., 2015). On the social side, the focus is on making students feel emotionally connected, fostering a sense of community, and encouraging interaction (Hodges & Cowan, 2012; Pacansky-Brock et al., 2020; Sheridan & Kelly, 2010; Wise, Chang, Duffy, & Valle, 2004). The teaching aspect centers on organizing content, guiding discussions, offering direct instruction, and giving timely feedback. Together, these elements ensure students feel supported and receive the guidance they need to learn. When combined, these constructs work in harmony to create an engaging online learning experience through the instructor's presence.

Research shows that pairing CoI-based practices with activities designed to boost self-efficacy yields positive gains on both instructional quality and student performance (Rosser-Majors et al., 2022; Holzberger et al., 2013). Faculty development programs informed by CoI and SET principles create the necessary scaffolding for instructors to enhance their instructor presence and meet the new RSI guidelines. Self-efficacy theory also offers a lens to evaluate how adjunct faculty perceive their ability to improve in this area. Consequently, not only do professional learning programs following these principles prepare faculty to teach online and tackle student performance challenges, but they also cultivate a sense of institutional belonging, ultimately strengthening the entire academic community.

Initial assessments at Southwest Community College revealed low retention rates for adjunct faculty, along with limited professional development opportunities. These factors led to a diminished sense of institutional belonging for online adjunct faculty. In response, we piloted an asynchronous training and instructional coaching program as part of a new onboarding initiative. Using data from student and faculty surveys, as well as coaching session transcripts, findings from the pilot shaped the development of a comprehensive instructional coaching program aimed at improving adjunct faculty readiness and bridging the performance gap between online and face-to-face courses. Informed by the Community of Inquiry (CoI) framework and Self-Efficacy Theory (SET), we designed a program that empowers faculty by strengthening their confidence and enhancing their instructor presence in their online classrooms.

Purpose of the Study and Research Questions

The purpose of this qualitative case study was to explore the impact of an instructional coaching program on adjunct faculty across different career stages in the community college setting. Instructional coaching is a collaborative, reflective process where a trained coach works with a faculty member to identify instructional goals, discuss teaching practices, and offer constructive feedback designed to enhance teaching self-efficacy and improve instructional effectiveness (Costa & Garman, 2016; Neff, 2024). Given the recent federal mandates to improve online course quality, the coaching focused on helping instructors boost instructor

presence in the online classroom while building self-efficacy through instructional coaching and iterative practice. This investigation was guided by the following research questions:

RQ1: How did participation in an Instructional Coaching Program (ICP) impact online adjunct instructor self-efficacy for enhancing instructor presence in the online classroom within a community college setting at different stages of their career (early career and mid- to late-career)?

RQ2: How and to what extent did participation in an Instructional Coaching Program impact the knowledge and skills of online adjunct instructors' ability to enhance instructor presence in the online classroom within a community college setting at different stages of their career (early career and mid- to late-career)?

Methods

Aligned with Yin's (2018) framework, we employed a multiple-case study design to thoroughly explore the intervention's impact on early-career (less than 7 years) and mid-to-late-career (more than 12 years) online adjunct faculty. Since the purpose of this qualitative study was to explore how adjunct faculty made sense of and demonstrated their learning, no control or comparison group was needed. The goal was to explore how instructors' self-efficacy evolved and was applied to their learning, with a particular emphasis on variation across career stages. To address the first research question, a deductive qualitative analysis was performed on a stratified random sample of course content, comparing the same course's materials before and after the intervention. To address the second research question, an inductive thematic analysis was conducted on coaching session transcripts to compare early-career (<7 years) and mid- to late-career (>12 years) online adjunct faculty's perceptions and experiences related to boosting instructor presence in their online courses.

Researcher Positionality

Stating the researchers' positionality, or personal and professional experiences related to the study, helped to establish how our perspectives might have influenced the research process and the results (Mertler, 2020). The first author, who led the study, has held various instructional design-related staff and leadership positions since 1997 in both K-12 and higher education contexts. She has also been an adjunct faculty member, teaching both online and in person, for over 20 years. Currently, she is the sole full-time instructional designer for SWCC's Teaching and Learning Center and served as a participant-observer while facilitating the online training and instructional coaching program. Through relationships developed during new faculty orientations, division meetings, and other collaborative projects, she was able to streamline the recruitment process while also building rapport and trust during the coaching sessions. The second author is a professor of learning design and technology, has taught online for over 20 years, and has designed and led multiple professional learning opportunities for faculty and K-12 teachers on online pedagogy. She served as a faculty mentor for the lead author. Due to our collective roles as scholar-practitioners, we were motivated to explore how online adjunct faculty develop self-efficacy to enhance instructor presence across career stages in the community college sector.

Participant Recruitment

After obtaining Institutional Review Board approval, the first author recruited SWCC adjunct faculty through voluntary participation using both a purposeful and convenience-based sample. Individual email invitations were sent to the 17 part-time faculty who met the following criteria: (a) instructors who taught an online course in fall 2023 and the same course in spring 2024, (b) those teaching part-time, and (c) those teaching a fully online course (Creswell & Guetterman, 2019). A total of four adjunct faculty members—all women from diverse disciplines and representing two distinct career stages—participated in the study. Two participants, Clara and Eliza (pseudonyms), were early in their careers, while Sophia and Evelyn (pseudonyms) were in their mid- to late-career stage. After obtaining informed consent, participants were asked to share their pre-intervention and post-intervention archived courses. We focused our analysis on course content, including assessment instructions, student feedback, discussion postings, assignment instructions, announcements, and other course messages. In addition, the first author conducted three coaching sessions per participant ($n = 12$) via Zoom between January and May 2024. Each session lasted approximately 30 to 45 minutes. They were recorded using Otter.ai and analyzed using Dedoose.

When participants were recruited, they were informed that all results would be reported anonymously, and coaching session conversations would remain confidential between the coach and participant. To further ensure privacy, we assured them that none of the session content would be shared with their supervisors. As a result, we decided to use pseudonyms, which the participants approved, allowing us to retain their ethnolinguistic backgrounds to honor their identities (Wang et al., 2024). Collectively, the selected participants provided valuable perspectives into the career-specific experiences, needs, and outcomes of the ICP (see Table 1).

Table 1

Participant Information

Case	Instructor Pseudonym	# Years Teaching	# Years Teaching Online	# Years Teaching at SWCC	Coaching Session Data	Pre- and Post Intervention Course Data
Early-career (<7 yrs.)	Clara	2	2	2	x	x
	Eliza	2	2	2	x	x
Mid- to late-career (>7 yrs.)	Sophia	27	18	25	x	x
	Evelyn	19	14	13	x	-

The early-career participants, Clara and Eliza, both started teaching two years ago. Clara taught a full course load as a part-time instructor at SWCC but did not intend to pursue full-time employment due to low pay and the high cost of living. She wanted to continue teaching as she held down a full-time job and attended graduate school. On the other hand, Eliza hoped to gain a more stable full-time community college instructor position while negotiating multiple responsibilities outside of work. Not surprisingly, they faced diverse challenges and motivations, a common experience among SWCC early-career adjunct faculty.

Alternatively, the mid- to late-career participants, Sophia and Evelyn, had extensive teaching experience with slightly different professional goals. Sophia brought a wealth of

college-level teaching and practical experience to her position, enriching the learner experience. Evelyn, who was a career adjunct instructor, had substantial experience teaching in both K-12 and community college settings and enjoyed working part-time while also pursuing her personal interests.

Intervention

The intervention consisted of a four-week online training program followed by three personalized coaching sessions. The training, [Humanizing Online Learning](#) was modified from an Open Educational Resource (OER) by Marcia Chaudet and colleagues (2024) titled “[Humanizing Virtual Learning](#),” which centered on cultivating awareness, empathy, trust, and presence in online learning. Structured modules emphasized topics like getting to know your learners, the importance of instructor presence and humanizing yourself, building a supportive community, and signaling presence through compassionate and constructive learner feedback. These behaviors (Richardson et al., 2015) are aligned with RSI requirements from the U.S. Department of Education. Following the training, three instructional coaching sessions were conducted to engage faculty in applying these strategies through reflective conversations, goal setting, resource sharing, and feedback.

Data Analysis

Archived Course Observations

To assess the intervention’s impact on participants’ knowledge and skills related to boosting instructor presence in the online classroom, we conducted a deductive content analysis with *a priori* codes from the Instructor Presence Codebook to compare pre- and post-intervention faculty-student interactions that were recorded in three sets of archived courses (Richardson et al., 2015, p. 259). For this study, knowledge refers to the participant’s conceptual understanding of effective practices for boosting instructor presence in the online classroom, while skills refer to the demonstrated ability to deploy these strategies in their online course to enhance instructor-student interaction. One participant’s course was excluded because the course modality was different (i.e., fully online and videoconference) between the fall and spring semesters. Interactions were examined from the Welcome modules, syllabi, online communications, discussions, assignment feedback, and announcements (Given, 2008). Due to limited access, all faculty-student communications that occurred outside of the learning management system (LMS) were excluded. A random sample of two items from the beginning (Weeks 1–4), middle (Weeks 5–11), and end (Weeks 12–16) of the course, along with all items in the Welcome module, was selected. Because not all courses had announcements or other interactions to catalog, the number of items differed for each course (Table 2). Consequently, 49 pre-intervention and 59 post-intervention course content items were analyzed.

Table 2

Content Analysis Document Frequency

^a Course	Pre-Intervention Sample Size	Post-Intervention Sample Size
Course 1A	14	21
Course 2B	21	23
Course 3P	14	15

Note. ^aCourse names are kept anonymous to protect the identity of instructors.

Coaching Session Transcripts

To explore the impact of the intervention on participants' self-efficacy for enhancing instructor presence in the online classroom, the first author used Braun and Clarke's (2006) thematic analysis process, which involved the following steps: (a) preparing, organizing, and cleaning the data; (b) reading through all the data; (c) summarizing key patterns at both broad and detailed levels; (d) developing and refining the coding framework through deductive and inductive methods; (e) coding the data; (f) grouping codes to form themes; and (g) interpreting the data.

In this case study, construct validity was established to ensure that key concepts were accurately defined, measured, and interpreted (Yin, 2018). To establish construct validity, we employed multiple strategies: (a) multiple sources of evidence, (b) a chain of evidence, (c) member checking, and (d) the use of clear operational definitions (Mertler, 2020; Yin, 2018). Data from coaching session transcripts, archived course observations, and field notes were triangulated to validate findings. To enhance reliability, we reviewed transcripts for mistakes, established standardized code definitions with examples to reduce subjectivity, and employed a critical friend to conduct four inter-rater reliability tests using Dedoose to evaluate code application consistency. Each test focused on four to five codes to minimize cognitive load. Inter-rater reliability was assessed using Dedoose, which calculated pooled Cohen's kappa scores ranging from 0.75 to 1.00, indicating substantial agreement and validating the coding scheme (Cicchetti, 1994; Fleiss, 1971).

Together, these strategies strengthened the representation of the constructs under study (Yin, 2018). However, the study did have limitations. First, we could not verify every action—such as emails or meetings—which affected the credibility of some claims. Also, the intervention consisted of a 4-week training followed by a 16-week semester, which was not enough time to fully understand the long-term impact. Finally, the number of participants was limited, with four women who served as adjunct faculty from the same institution. As a result, this limited our ability to generalize the findings. As with most qualitative studies, the findings offer valuable insight regarding adjunct faculty growth; however, it is possible the observed changes occurred due to other contextual factors rather than as a direct result of the intervention. Despite these drawbacks, we believe this study shares important insights about a comprehensive instructional coaching program aimed at improving the instructor presence of adjunct faculty who teach online.

Results

Intervention Impact on Self-Efficacy

Using a multiple case study design, we present a cross-case comparison of the early-career (<7 years) and mid- to late-career (>12 years) cases according to our two research questions. To address the first research question on the impact of an ICP on self-efficacy for enhancing instructor presence in an online setting, we conducted an inductive thematic analysis of coaching session transcripts. This analysis compared the perceptions and experiences of early-

career (<7 years) and mid- to late-career (>12 years) online adjunct faculty regarding their efforts to boost instructor presence in the online teaching environment.

The results revealed that participation in the ICP positively influenced the development of self-efficacy in online adjunct faculty, heightening instructor presence in the online classroom across all career stages. Six themes were uncovered related to the development of participants' self-efficacy for enhancing instructor presence in the online classroom: (a) behavioral steadfastness, (b) awareness and aspiration, (c) exploration and learning, (d) practice and development, (e) belief and confidence, and (f) goal setting and planning (Table 3). Each theme had at least 10 excerpts, providing sufficient data to examine how instructors enhanced their instructor presence across different self-efficacy categories.

Table 3

Self-Efficacy Themes Identified from Coaching Session Transcripts

Theme	Sub-theme Components	Definition	Examples
Behavioral steadfastness	No plans to change	Participants definitively stated they have no intention of trying something new or planning to change how they currently do things in their course.	"I don't rate things that way. I don't think that way." "I don't like pictures, and I don't feel comfortable with pictures."
Awareness and aspiration	Acknowledgment of limitations Anticipating students' and/or teacher needs Open to new ideas Personal reflections	Participants were aware of a new strategy and willing to consider trying it.	"And I said to myself, you know, tone is so important, because they don't see you on a daily basis...But, like a positive, encouraging tone means everything to someone who is searching for...How am I doing? You know?"
Exploration and learning	Learning new skill Learning by observing Seeking guidance Showing hesitation	Participants explored and learned about a new strategy	"...Chat GPT was astounding to me...I couldn't believe what it could do...I even had it write poetry...I was amazed with...how it changes the tone of what...you're writing."
Practice and development	Practicing new skill Setback Making adjustments Achieving success	Participants actively practiced and developed a new strategy.	"I tried...[strategy]... and no one showed up." "So I've been tweaking based on what they tell me in my reflection pieces."

Theme	Sub-theme Components	Definition	Examples
Belief and confidence	Optimistic and affirmative statements Belief in ability to positively impact student learning Perceived confidence Recognition of impact	Participants believed they could perform a new strategy or were confident in their ability to do so.	"But I feel like I've come a really...long way. And I love it,... now I feel like I teach better online than I would in person." "Maybe I like the clarity of it...I'm hoping that this will help ...stop any confusion with students..."
Goal setting and planning	Planning to do	Participants set goals or planned to use a new strategy.	"I want at least one weekly video." "I want to use the [Gen]AI function more to rewrite my comments with a more positive tone, and I want to do that more frequently."

Each of the six themes are further described and discussed in the following section.

Theme One: Behavioral Steadfastness

The *behavioral steadfastness* theme highlighted participants' definitive statements about their reluctance to try new methods in their online teaching practice. For instance, one participant explained her discomfort and unwillingness to use video on Zoom when she shared, "I don't want to do video." This statement reflected her resistance to changing her behavior, as the participant showed no intention of adopting new strategies or modifying her existing approaches. The theme of behavioral steadfastness encapsulated a resistance to change, demonstrating how participants' current beliefs and attitudes towards teaching practices remained firmly rooted, with no plans to alter their methods.

Theme Two: Awareness and Aspiration

The second theme, *awareness and aspiration*, was evident when participants critically reflected on their own limitations, the anticipation of both student and teacher needs, and an openness to new ideas. As Clara shared, "And I said to myself, you know, tone is so important, because they don't see you on a daily basis...But, like a positive, encouraging tone means everything to someone who is searching for...How am I doing? You know?"

Clara's statement exemplified the depth of personal reflection, demonstrating self-efficacy in her capacity to learn and grow while thinking about how she could improve in the future. By anticipating the needs of her students and acknowledging the importance of using a warm tone in her communications, she showed a readiness to enhance her teaching practice. The theme of awareness and aspiration reflected a growth mindset, emphasizing participants' commitment to critically reflect on their personal and professional growth.

Theme Three: Exploration and Learning

The third theme, *exploration and learning*, highlighted the process participants took as they acquired new skills. This process involved observing others, seeking guidance, and occasionally showing hesitation. Evelyn reflected on her experience when she stated “...ChatGPT was astounding to me...I couldn't believe what it could do...I even had it write poetry...I was amazed with...how it changes the tone of what...you're writing.” Her observation of the capabilities of Generative Artificial Intelligence (GenAI) illustrated her openness to trying new strategies. As she explored the possibility of using the new strategy, she also sought guidance and experienced hesitation. This willingness to experiment led to continual learning where participants developed confidence in embracing innovative teaching strategies.

Theme Four: Practice and Development

The fourth theme, *practice and development*, emphasized how participants actively engaged in practicing new skills by encountering setbacks, making necessary adjustments, and ultimately achieving success. Evelyn shared how she “incorporated a personal story” as she practiced a new strategy, whereas Sophia mentioned that she tried a new strategy, and no one showed up. Eliza expressed how she “noticed this week...that...a lot more...or maybe...a handful of [students] consistently completed by Friday.” Each of these quotes illustrated the participants’ dedication to their personal growth, as evidenced in their persistence in performing new strategies. Moreover, they demonstrated persistence by continually refining their techniques and overcoming challenges.

Theme Five: Belief and Confidence

The fifth theme, *belief and confidence*, was characterized by optimistic and affirmative statements, a strong belief in the ability to positively impact student learning, perceived confidence, and recognition of the impact on student learning. Perceived confidence represents an individual’s belief in their power to influence what happens in their lives (Bandura, 2010). Through their perceived confidence and an optimistic demeanor, participants consistently demonstrated a belief in their ability to positively influence student learning while also recognizing the positive impacts of their changes. For example, Eliza said, “But I feel like I've come a really...long way. And I love it,... now I feel like I teach better online than I would in person.” This statement exemplified Eliza’s perception in her ability to effect change in how students learn, giving her a sense of agency. Eliza also noted, “Maybe I like the clarity of it...I'm hoping that this will help ...stop any confusion with students...” This statement highlighted Eliza’s belief in the effectiveness of her new strategies and her commitment to enhancing student understanding. She firmly believed in her ability to positively influence student learning and began to recognize some of the impacts of the changes she was making. The theme of belief and confidence demonstrated the participants’ positive outlook and confidence in their teaching abilities, which exhibited a strong sense of self-efficacy.

Theme Six: Goal Setting and Planning

The sixth theme, *goal setting and planning*, illustrated a high level of self-efficacy to transfer new knowledge and abilities to different contexts, such as a future or different course. With newly acquired knowledge and skills, the participants planned and set goals to improve their teaching practice. Evelyn shared, “I want at least one weekly video,” indicating a specific goal to enhance student engagement through regular video updates. She also commented, “I want to use the [Gen]AI function more to rewrite my comments with a more positive tone, and I want

to do that more frequently.” This sentiment indicated her intention to use GenAI to improve the quality and tone of her feedback. The theme of goal setting and planning focused on the participants' beliefs in their ability to improve student learning through strategic planning and deliberate action.

Cross-Case Thematic Analysis Findings - Comparing Early- and Mid- to Late-Career

Adjunct faculty, regardless of career stage, exhibited diverse degrees of self-efficacy in enhancing instructor presence in their online courses. Through the lens of five themes—awareness and aspiration, exploration and learning, practice and development, belief and confidence, and goal setting and planning—early-career and mid- to late-career faculty navigated unique challenges and opportunities in their professional learning.

Early-career adjunct faculty adeptly balanced their own time constraints with their students' diverse needs, demonstrating optimism and openness to strategies that improved course design and student engagement. Comfortable with technology, they applied new skills and engaged in continuous practice, making iterative improvements based on student feedback. Their confidence grew as they observed repeated positive outcomes impacting student learning. Looking forward, they planned to apply these insights in future courses, highlighting the intervention's positive influence on their self-efficacy and instructor presence in the online classroom.

Mid- to late-career adjunct faculty exhibited self-efficacy for boosting instructor presence by recognizing their limitations, anticipating needs, and engaging in personal reflection, which contributed to their professional growth. While very cautious, they explored new skills and made necessary adjustments to their teaching practices, showing a preference for direct, step-by-step instruction. Much of their perceived confidence stemmed from their prior face-to-face teaching experiences and did not easily translate to the online environment. However, their optimistic outlook and belief in their ability to positively impact student learning by enhancing their instructor presence in their online classroom demonstrated their commitment to continuous improvement. Due to personal and professional challenges, they struggled to fully implement their intended changes, leading to fewer mastery experiences compared to early-career participants.

Intervention Impact on Knowledge and Skills

To address the second research question, which examined how the ICP impacted adjunct instructors' knowledge, skills, and ability to enhance instructor presence in their online classrooms, a deductive, qualitative analysis was conducted using a stratified random sample of course content, revealing the type, degree, and quality of interactions between the instructors and their students. This analysis compared content from the same course taught by each instructor in two different semesters—one in the fall before the intervention and one in the spring after the intervention.

Cross-Case Content Analysis Findings

The content analysis of pre- and post-archived courses revealed more observable instructional behaviors, actions, and practices that enhanced instructor presence in the online classroom. Early-career participants benefited the most, showing increases in two of the three

foundational constructs of CoI — social presence (128.6%) and teaching presence (45.5%). For early career participants, the greatest improvements in teaching presence were observed in direct instruction, facilitating discourse, assessment, and design and organization. In addition, the greatest increases in social presence were observed in the cohesive, interactive, and affective sub-elements of the social presence domain.

Specifically, early career participants focused on integrating more emotion into their written communications by using greetings and salutations and addressing students by their first names (221.4%; Table 4). They also aimed to tap into the students' socio-emotional nature by more frequently acknowledging students' concerns and feelings (288.9%) and offering encouragement (166.7%). Much of their effort involved redesigning assignment instructions using the TILT (i.e., Transparency in Teaching and Learning) framework to improve clarity in instructions and grading expectations (52.8% and 66.7%, respectively). Additionally, they improved how they explained concepts, topics, and processes (860.0%).

Table 4

Percent Change in Early-Career Adjunct Faculty's Most Impactful Codes

Element	Sub-Element	Codes	Pre	Post	% Change (#)	+/-
Social	Affective (AF)	AF-Emotion	40	89	122.5% (n = 49)	+
Social	Cohesive (CO)	CO-Greetings and Salutations	34	122	258.8% (n = 88)	+
		CO-Name	14	45	221.4% (n = 31)	+
Social	Interactive (I)	I-Acknowledge	9	35	288.9% (n = 26)	+
Teaching	Assessment (AS)	AS-Info	33	55	66.7% (n = 22)	+
Teaching	Design & Organization (DE)	DE-Clarify	36	55	52.8% (n = 19)	+
Teaching	Facilitating Discourse	FD-Encourage	24	64	166.7% (n = 40)	+
Teaching	Direct Instruction	DI-Clarify	5	48	860.0% (n = 43)	+

In contrast, Sophia, the only mid- to late-career instructor with a complete set of courses available for analysis, experienced a decrease in instructor presence codes post-intervention. She focused on developing her teaching presence more than social presence, making slight gains in course design and organization, facilitation of discourse, and direct instruction. While she made slight gains in teaching presence, Sophia experienced decreases in both the affective and cohesive sub-elements of social presence, with no change in the interactive sub-element.

For Sophia, noticeable declines were observed in self-disclosure, warmth in her communications, the use of greetings and salutations, and references to students by name (Table 5). There was also a decrease in communication related to her availability to meet with students. These declines suggested a reduction of course evidence illustrating the instructor's ability to make emotional and social connections with her students in her online course. Most of the increases related to teaching presence included improvements in course design and organization, assignment instruction (134.8%), clarification of grading expectations (67.6%), just-in-time course updates (27.3%), clearer guidance on submitting assignments and finding course resources (31.3%), and more due date reminders (32.5%). In addition, there was a slight increase (10%) in communications where she provided tips about how students could succeed in the course, as well as in the number of prompts encouraging student responses.

Table 5*Percent Change in Sophia's Most Impactful Codes*

Presence	Domain	Codes	Pre	Post	% Change	+/-
Social	Affective (AF)	AF-Self-Disclosure	42	26	-38.1%	-
		AF-Warm	43	24	-44.2%	-
Social	Cohesive (CO)	CO-Greetings and Salutations	101	63	-37.6%	-
		CO-Name	36	18	-50.0%	-
Teaching	Design & Organization (DE)	DE-Avail	40	11	-72.5%	-
		DE-Clarify	23	54	134.8%	+
		DE-Info	33	42	27.3%	+
		DE-Navigation	32	42	31.3%	+
		DE-Establishing time parameters	40	53	32.5%	+
		DE-Designing Methods	45	31	-31.1%	-
Teaching	Facilitating Discourse	FD-Tips	20	22	10.0%	+
		FD-Prompt	0	21	N/A	+
Teaching	Assessment (AS)	AS-Info	34	57	67.6%	+

Discussion and Recommendations

Practical Implications for Adjunct Faculty Development

Based on the results of this study, it was evident that differentiated faculty development programs customized to the needs of early-career and mid- to late-career adjunct faculty are a worthwhile endeavor. While instructional coaching showed promise in fostering noticeable improvements in instructor presence across various career stages, alternative approaches where one-on-one coaching is not possible may be needed. For example, peer mentoring or structured learning communities could complement asynchronous training to meet similar goals, deepening critical reflection, building self-efficacy, and supporting RSI compliance.

Early-career participants gained the most, showing increases in two of the three foundational constructs of CoI—social and teaching presence. As a result, early-career adjunct faculty programs should emphasize the integration of new technologies and innovative

pedagogy. The findings indicated that early-career participants had greater gains in instructor presence by using tools like GenAI-assisted course design, the TILT framework, and personalized feedback.

Given these findings, institutions should consider emphasizing experimentation with new technologies and cutting-edge teaching practices. Doing so not only supports professional growth but also helps foster engaging online learning environments that comply with RSI requirements.

In contrast, the mid- to late-career instructors focused more on developing their teaching presence more so than their social presence. Professional growth programs for mid- to late-career adjunct faculty may need to focus on refining existing practices and providing opportunities for mentorship roles. This study found that the mid- to late-career faculty, while initially hesitant to adopt new strategies, implemented practices centered on setting clear expectations on participation, assignments, discussions, and other student behaviors in an online course. While the course records showed a decline in evidence of instructors making social and emotional connections, coaching session conversations revealed that these connections occurred through face-to-face interactions, emails, and telephone calls. However, these methods did not leave a trace in the online course materials, possibly masking the results. Additionally, both mid- to late-career faculty members preferred hands-on, step-by-step instruction when learning new technologies. Despite this, they had extensive experience in critical reflection and recognized the importance of connecting with students both academically and personally. While they needed opportunities to refresh their technological skills, they were also excellent candidates for mentorship roles, offering valuable guidance to early-career adjuncts.

Tensions in Faculty Growth in Online Teaching

Although the coaching sessions contributed to enhancing self-efficacy for boosting instructor presence in the online classroom, they also uncovered key challenges and tensions, which influenced adjunct faculty experiences. The following tensions revealed some of the complexities associated with adopting effective practices in online teaching and offered insight into navigating participants' journeys.

Time Management

One of the biggest challenges participants faced was time management. Juggling full-time work, graduate school, family care, and teaching multiple classes—often at more than one college—significantly limited participants' ability to implement their desired improvements. Despite their willingness to enhance instructor presence, they struggled to maintain a growth-oriented approach due to time constraints. They faced challenges in providing timely feedback, often extending response times to two or more weeks, which left them disheartened. Additionally, they tended to spend more time focusing on students who needed support while giving less attention to those who had been performing well. Clearly conscientious in their efforts to support student learning, all participants struggled with the practical issues related to time constraints.

Integration of GenAI

The potential of using GenAI for administrative tasks—such as creating rubrics, assignment instructions, and assessments—as well as for enhancing instructor communications

to make them warmer and more engaging, was met with conflict. On the one hand, participants were excited to use GenAI. In fact, integrating its use in the online training seemed to boost self-efficacy for most participants. It was described as a “game changer” for improving clarity and tone. One dilemma arose between teaching students how to use GenAI tools effectively while also ensuring they maintained their ability to engage in the learning process. Several participants recognized how valuable and ubiquitous GenAI was and would be in their students’ futures, but they all feared students would miss out on learning how to learn. However, integrating GenAI into faculty development training—without making it the central focus—proved highly effective. By learning to craft effective prompts, participants found that GenAI helped them improve their teaching while fostering deeper student learning.

Student Engagement Challenges

Another tension involved the relationship between participants’ self-efficacy and level of student engagement. When participants perceived a low level of student engagement and motivation, they were more likely to question the effectiveness of their efforts, leading to a range of emotions from patience to frustration and discouragement. When students delayed or failed to respond, participants’ confidence in developing meaningful relationships with their students declined, underscoring the dynamic relationship between self-efficacy and external validation.

Balancing Instructor Presence and Student Autonomy in Online Discussions

Participants also shared how they chose to encourage student autonomy in the online discussions. Several participants recognized the need to facilitate and guide student learning to meet RSI guidelines, but they worried their presence would stifle self-directed learning. This presents a methodological challenge because RSI specifies that instructors participate in the discussions (as one of the options to demonstrate substantive interactions). At the same time, excessive instructor presence in the discussions can impede student-to-student interactions, limit student independence, and undermine the social nature of peer learning (Mazzolini & Maddison, 2007; Zhao & Sullivan, 2017). This tension underscores the broader challenges related to the delicate balance between fulfilling regulations and promoting student ownership of their learning.

Digital Divide and Overcoming Transactional Distance

Transactional distance surfaced as another tension, primarily for mid- to late-career faculty. For example, one participant admitted to relying solely on email and the telephone while avoiding other forms of video-based communication due to her deep discomfort with technology. This limited her effectiveness in interacting with students online. Having started her career as a traditional in-person instructor, she struggled to find ways to connect with students without relying on visual cues or body language. Consequently, she preferred to meet with students in person or over the phone, whereas many of her students preferred to only communicate via chat or Zoom. This created a methodological dilemma as she searched for new strategies to connect with her students using her familiar in-person methods.

Personalization Versus Scalability

The tension between personalization and scalability also surfaced, particularly for those participants who valued one-on-one personal interactions with their students but recognized that such connections do not necessarily scale, placing additional strain on their workload. Participants wanted to make personal connections, but they lacked the time or office space to do so. This desire to form meaningful relationships while balancing course loads and other responsibilities, likely influenced their belief in their ability to fully embrace effective strategies for enhancing instructor presence.

Recognizing Institutional Barriers to Implementation

Overcoming institutional policies and constraints further complicated participants' ability to successfully implement effective practices that meet RSI requirements. One participant faced limitations due to her inability to modify the master course template. Additionally, institutional challenges, such as human resource policies that limit adjunct faculty work hours, are crucial for the success of early- and mid- to late-career faculty development programs. Many community colleges limit adjunct faculty workloads to avoid the costs associated with providing retirement and health care coverage; however, policies vary by state. This limitation, combined with a shortage of adjuncts, often forces colleges to prioritize filling courses over offering the extra hours associated with professional development. As a result, faculty participation in professional development is hindered. These challenges reflect broader systemic issues that impede adjunct faculty from fully contributing to institutional goals and positively impacting student learning. To effectively support the growth and success of adjunct faculty professional development programs, these barriers and tensions need to be addressed.

Acknowledging these tensions and challenges provides valuable insights into the lived experiences of adjunct faculty as they balance their well-being while pursuing their professional growth and improving student learning. These insights reveal the need for institutional support, tailored faculty development, and intentional course design to enable faculty to strengthen their instructor presence to meet RSI requirements. By addressing these issues, institutions can empower faculty to overcome obstacles, excel in their practice, and deepen student learning.

Conclusion

Community colleges play multiple roles in higher education, serving millions of diverse students through dual enrollment, adult education, GED preparation, transfer degrees, and workforce training (CCRC, 2021). Yet, one critical challenge for community colleges relates to the recruitment and retention of qualified adjunct faculty, particularly in the current economic climate of high inflation and exorbitant cost-of-living expenses. As the demand for online instruction grows, providing professional development to adjunct faculty plays a critical role in the success of the institution. To integrate and support adjunct faculty, institutions need to address their precarious working conditions and limited growth opportunities.

Findings from this study suggest that combining instructional coaching with online training can strengthen adjunct faculty's self-efficacy and help them boost their instructional presence in the online learning environment. By supporting adjunct faculty at different career stages, the program's positive impacts were evident, as were key tensions that influenced faculty growth and retention. These findings suggest that when community colleges provide

opportunities for adjunct faculty to connect and learn from each other, it fosters stronger, more fulfilling relationships, thereby increasing their sense of belonging (Thirolf, 2016). Decades of research tell us that a “well-developed sense of identity, confidence, and sense of purpose in our students is correlated with academic achievement and overall student success” (Thirolf, 2016, p. 307). Similarly, fostering a strong sense of belonging among adjunct faculty would likely improve their retention rates, satisfaction, and overall engagement, ultimately leading to improved outcomes for student learning.

Community college leadership needs to explore and implement faculty engagement models that reduce turnover and enable faculty members to develop meaningful and lasting relationships with their students. These relationships can have a profound impact on students beyond their educational journey, extending into their professional careers. By investing in adjunct faculty, community colleges can better serve their community and students while enhancing the livelihoods and well-being of adjunct faculty—both key to institutional success.

Declarations

The authors declare no conflicts of interest.

This research was approved by the Arizona State University Institutional Review Board (IRB Protocol HRP503Z, approved March 3, 2023). All participants provided informed consent prior to data collection. Participation was voluntary, and all data were de-identified and stored securely to protect confidentiality in accordance with institutional guidelines.

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HyFlex Graduate Education: A Systematic Review

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Abstract

This paper presents the findings of a systematic literature review examining HyFlex instruction in graduate education over the past decade. The study aims to synthesize existing research on how universities are addressing the diverse needs of their graduate students through HyFlex instruction. This systematic review provides a comprehensive analysis of current research trends, including the distribution of publications over time, publication outlets, geographic location, and author affiliations. Additionally, it explores the research purpose, subject-matter domains, methodologies, and outcomes associated with HyFlex instruction in graduate education. Using updated PRISMA guidelines, the researchers conducted a systematic search across five databases. Ultimately, 28 peer-reviewed journal articles met the inclusion criteria. The findings reveal a growing body of literature on HyFlex instruction in graduate education, spanning diverse subject areas and employing various research methodologies. Key areas of focus include graduate students' academic performance, interaction channels, class attendance, attentiveness, engagement, perceived satisfaction, and dimensions of dialogue. Other studies examined faculty perspectives on HyFlex instruction, particularly in relation to technology design, instructional design, organization and logistics, and skills and attitudes. Although HyFlex teaching gained significant traction during the COVID-19 pandemic, this review highlights the need for further research into its long-term relevance and effectiveness in a post-pandemic educational landscape.

Keywords: Hybrid flexible instruction, HyFlex, graduate education, systematic review, online learning

Romero-Hall, E., Allen, E., Morris, A.A., Duan, Y., & King, A. (2026). HyFlex graduate education: A systematic review. *Online Learning*, 30(2), 271-301.
<https://doi.org/10.24059/olj.v30i2.5001>

The increased presence of online learning is one of the most prominent manifestations of educational evolution at all levels. Hodges et al. (2020) posits that online education has experienced unprecedented growth, offering learners flexibility, accessibility, and opportunities for personalized learning experiences. From K-12 to higher education, institutions are harnessing the power of digital platforms to deliver content, facilitate discussions, and engage students in diverse learning activities (Picciano, 2017). However, the efficacy and scalability of online learning has been a subject of ongoing debate, with proponents highlighting its potential to democratize education and critics raising concerns about issues of equity, engagement, and academic integrity (Hodges et. al, 2020). Moreover, online education in higher education has been a dynamic and transformative force reshaping the traditional paradigms of teaching and learning. Ali (2020) highlights that with the advent of digital technology and the proliferation of Internet connectivity, online education has become increasingly prevalent in higher education institutions worldwide.

One of the most significant benefits of online education in higher education is its flexibility (Sun & Chen, 2016). Unlike traditional classroom-based instruction, asynchronous and HyFlex online courses allow students to engage with course materials at their own pace and convenience. This flexibility is particularly advantageous for non-traditional students, such as working professionals, parents, and individuals with busy schedules, who may struggle to attend regular classes on campus. By removing the constraints of time and place, online education empowers students to pursue higher education while balancing other commitments.

Within the realm of higher education, the concept of HyFlex learning has emerged as a hybrid approach that combines the best elements of traditional and online instruction. HyFlex learning environments allow students to seamlessly choose between attending classes in person, participating remotely, or accessing asynchronous learning materials, thereby accommodating diverse learning preferences and schedules (Beatty, 2019). Beatty (2019) suggests that this flexible model holds promise for enhancing student engagement, promoting active learning, and optimizing resource utilization within educational institutions. As educators and policymakers navigate these transitions to alternative modalities of learning, it becomes imperative to critically examine the opportunities and challenges associated with each approach (Aldosemani, 2023). The aim of this systematic review is to delineate the main characteristics of the scientific literature pertaining to HyFlex learning in graduate education.

Literature Review

Today students may face many barriers in completing their education at traditional brick and mortar institutions (Beatty, 2019; Bower et al., 2015; Goldrick-Rab, 2023; Irvine, 2020; Seaman et al., 2018). In 2023, an estimated one in five undergraduate students in the United States were raising a dependent child, 59% had full time employment outside of their studies, and 11% were working two or more jobs (Goldrick-Rab, 2023). Lack of childcare and changes in life circumstances often lead to students not completing their education (Rosen, 2021). Many students are geographically isolated (Caparas & Yango, 2023; Cunningham, 2014; Lakhal et al., 2021; Norberg, 2012; Olelewe & Agomuo, 2016; Wong, et al., 2023) and lack reliable transportation (Rosen, 2021).

Similar to asynchronous online learning, HyFlex instruction offers universities the opportunity to promote equity in education for students who otherwise would be unable to attend (Beatty, 2019; Bower et al., 2015; Caparas & Yango, 2023; Cunningham, 2014; Irvine, 2013; Lakhal et al., 2021; Norberg, 2012; Olelewe & Agomuo, 2016) and allows for the flexibility to prevent students from dropping out due to circumstances such as illness and unforeseen life events (Li et al., 2022; Zydney et al., 2020). Research has pointed to HyFlex instruction as a way to provide an equitable learning environment (Imran et al., 2023) that allows for diverse learners (Olelewe & Agomuo, 2016) to achieve high levels of student engagement (Irman et al., 2023; Wong et al., 2023) without sacrificing high quality learning (Irman et al., 2023) and live social interactions with peers and instructors (Romero-Hall & Vicentini, 2017). The benefits of a HyFlex learning environment not only apply to the students, but also to the institutions. By offering HyFlex classes, institutions can accommodate increased enrollment (Howell, 2022), enabling students who are unable to attend in-person classes to participate through online learning modalities, such as remote participation or accessing asynchronous learning materials. With instructors simultaneously able to teach two groups of students, online and in-person, institutions can also see decreased infrastructure cost (Howell, 2022; Irman et al., 2023).

HyFlex instruction, while offering flexibility and inclusivity, is not without its challenges. One significant issue involves the psychological difficulties faced by students in HyFlex settings, such as struggles with social interaction (Howell, 2022; Irman et al., 2023; Wong et al., 2023). Research highlights a frequent lack of natural communication and meaningful social interactions between distance learners and their in-person counterparts. These psychological challenges are often compounded by physical and technological barriers, such as the complexities of arranging classroom environments to effectively integrate online participants (Howell, 2022; Irman et al., 2023; Wong et al., 2023). Privacy concerns also emerge as a critical issue. Some technologies employed in hybrid or HyFlex settings have questionable privacy safeguards (Blackmon & Major, 2023) which can negatively influence students' perceptions of the learning environment. Additionally, the unique demands of HyFlex instruction place significant strain on faculty who are already managing heavy workloads. Research by Romero-Hall and Ripine (2021) underscores that faculty members do not feel prepared to manage the intricacies that are unique to HyFlex instruction. Furthermore, instructors have consistently underscored the importance of robust institutional support and adequate resources, which are often insufficient, for the successful design and implementation of HyFlex courses (Morris, 2025).

With HyFlex educational environments offering so many potential benefits, it is important that institutions have access to the breadth of research conducted on the subject. Currently systematic reviews and meta-analysis have been conducted on many topics related to technology education. Bervell and Umar (2017) investigated the use of learning management systems in higher education. Amaechi et al. (2022), Imran et al. (2023), and Zhou et al. (2023) researched how teaching in higher education changed during the COVID-19 pandemic. These systematic reviews referenced HyFlex settings, but the modality was not the central focus, resulting in a lack of a targeted attention to HyFlex research.

Several systematic reviews have explored HyFlex instruction, providing valuable insights into its implementation and impact across various educational contexts (Barr & Luo, 2025; Chen & Lai, 2024; Cumming et al., 2024; Howell, 2022; Mahrishi et al., 2025; Romero-Hall et al.,

2025; Wong et al., 2023). Wong et al. (2023) conducted a comprehensive review examining the benefits, challenges, and existing research on HyFlex instruction across all education levels (i.e., elementary, secondary, and higher education). Other reviews have focused specifically on higher education settings. Howell (2022), Chen and Lai (2024), Cumming et al. (2024), Mahrishi et al. (2025), and Barr and Luo (2025) focused their systematic reviews on HyFlex instruction within higher education, analyzing research literature that comprised both undergraduate and graduate education. Howell's review identified three major themes in studies published between 2011 and 2021: definitions and purposes of HyFlex instruction, implementation strategies for educators, and future research directions. While Howell's work primarily targeted higher education institutions, it emphasized the application of HyFlex settings in research contexts. Chen and Lai (2024) narrowed their focus to interdisciplinary English courses, reviewing studies published between 2008 and 2023 to explore HyFlex instruction within this specific domain. The results pointed to deficiencies, including a lack of framework to assess higher order thinking skills in interdisciplinary English courses, and challenges facilitating meaningful discourse across modes. Cumming et al. (2024) examined the experiences of university instructors and students with the HyFlex model through a systematic review. Their findings highlighted a lack of research emphasizing instructors' perspectives while also addressing learning satisfaction, benefits, barriers, challenges, and external factors influencing teaching and learning in HyFlex environments. Mahrishi et al. (2025) mapped research dissemination on the HyFlex model in higher education from 2018 to 2023. Their review identified trends in research output, geographical distribution of scholarly work, influential authors, and critical themes such as the need for ongoing infrastructure adaptation and digital tools. Barr and Luo (2025) contributed by analyzing learning outcomes, challenges, beneficial technologies, and instructional strategies specific to higher education contexts. Most recently, Romero-Hall et al. (2025) conducted a systematic review focusing on HyFlex instruction in undergraduate education. Their work provided detailed instructional and learning strategies tailored to the needs of this student population.

This paper presents a systematic review as part of a broader, comprehensive examination of HyFlex instruction in higher education. The overarching research explores its implementation, effectiveness, and pedagogical implications across various educational levels, including the previously mentioned systematic review of HyFlex instruction in undergraduate education (Romero-Hall et al., 2025). While the overarching research encompasses a wide range of contexts, this specific systematic review focuses exclusively on HyFlex instruction within graduate programs. By narrowing the scope to the graduate context, this study aims to uncover how HyFlex instruction is uniquely applied in graduate education, where students often (a) navigate distinct challenges such as balancing professional, academic, and personal responsibilities, (b) engage with coursework that demands advanced critical thinking skills, (c) are often building their professional identity, and (d) are asked to apply theoretical knowledge to real-world problems as part of their coursework. The findings from this focused review will complement the broader research by providing deeper insights tailored to the graduate experience.

Purpose Statement & Research Questions

By systematically analyzing existing literature, this review intends to shed light on the evolution of HyFlex learning research. It also examines how universities are leveraging this

approach to address the diverse needs of their graduate student population. This systematic review explores current trends in peer-reviewed literature on HyFlex learning between 2013-2023, with a particular focus on its application within graduate education. This study addresses the following research questions:

- What were the main characteristics of the scientific literature on HyFlex learning in graduate education, considering factors such as year of publication, publication outlets, number of authors, geographical distribution, subject-matter domains, and number of participants?
- What are the major research methodologies, funding sources, and research outcomes in studies of HyFlex learning in graduate education?

Methods

A systematic review (Newman & Gough, 2020) was conducted to answer the research questions and synthesize information for future researchers and practitioners. A systematic review is an in-depth literature review that seeks to comprehensively locate research conducted on a topic and synthesize the findings to present an overview of current research methods and findings (American Psychological Association, 2016).

This systematic review adheres to Beatty's (2019) definition of HyFlex instruction, which combines online and on-ground (classroom-based) students in the same class session. The researchers also acknowledge that the term *HyFlex instruction* is often used interchangeably with other terms in the literature, such as hybrid synchronous instruction (Romero-Hall & Vicentini, 2017), blended synchronous learning (Hastie et al., 2010), synchronous online teaching (Park & Bonk, 2007), and synchronous hybrid delivery (Butz et al., 2014). Each study included in this review was meticulously examined by the research team to ensure alignment with Beatty's (2019) principles of HyFlex instruction.

Search Strategy

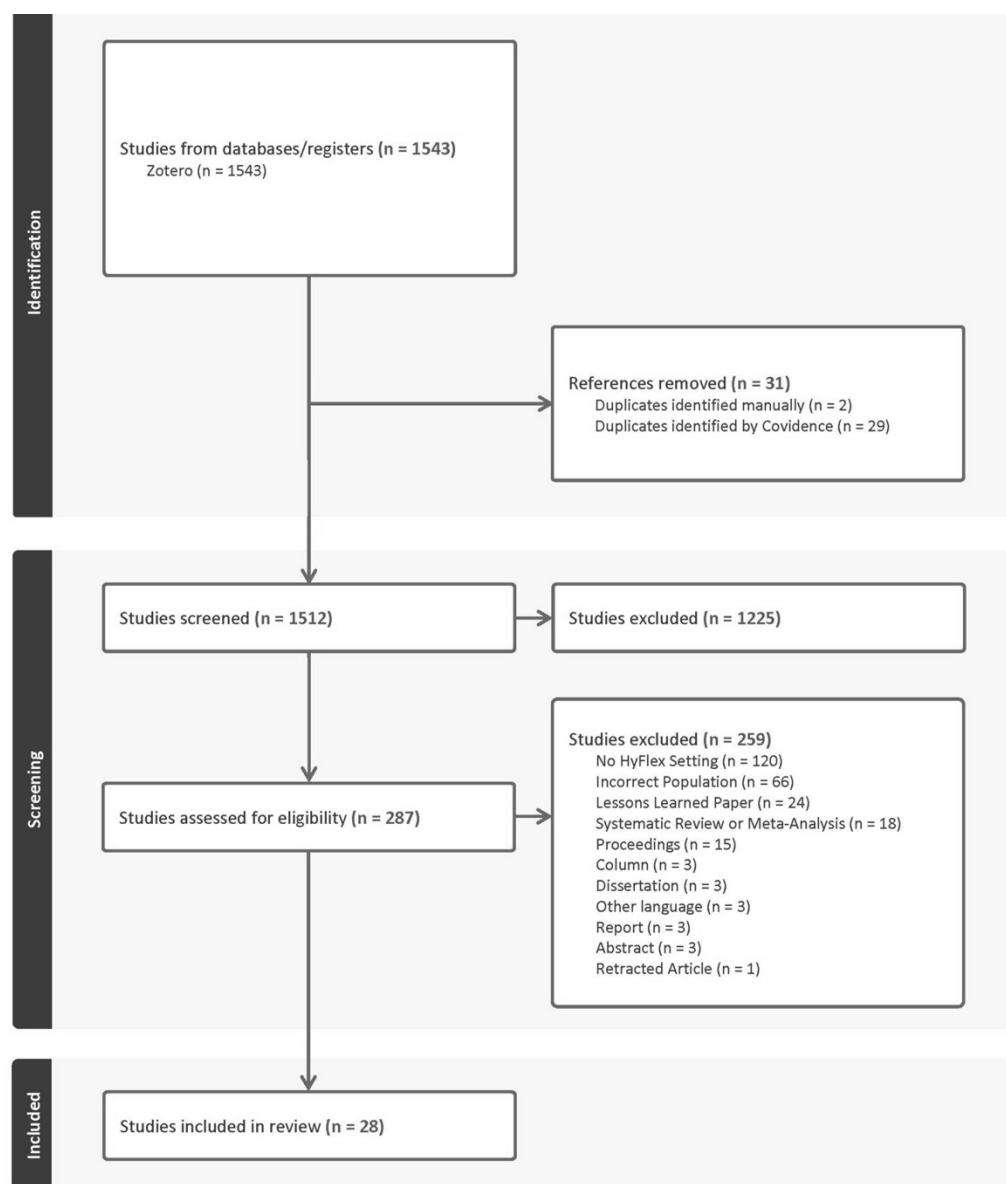
Researchers followed updated PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) principles (Page et al., 2021) to conduct this systematic review to offer transparency in research procedures and adhere to evidence-based protocols (see Figure 1). A search of literature on HyFlex instruction was conducted using electronic databases. The search for journal articles for the systematic review was conducted in November 2023. Five databases were searched: ERIC, Education Source, Academic Search Complete, Web of Science, and Scopus. After a consultation with an institutional librarian, these specific databases were selected for the systematic review because they could provide access to education-related research published in peer-reviewed publications.

Similar to the procedure described in Romero et al. (2025), the following search terms were used across all five databases to search within the title, descriptors, keywords, or abstracts: (*HyFlex* OR *blended synchronous* OR *hybrid synchronous* OR *synchronous online* OR *synchronous hybrid*) AND (*learning* OR *instruction* OR *courses* OR *teaching* OR *delivery*),

(*multimodal instruction*), and (*multimodal learning*). These search terms were chosen as they are words commonly used when referring to HyFlex learning. These searches were cross-searched with the following search terms: *higher education* OR *university* OR *college* OR *tertiary education* OR *post-secondary* OR *postsecondary*.

Figure 1

PRISMA Diagram



Inclusion & Exclusion Criteria

The review was guided by specific inclusion criteria, which articles were required to meet in order to be considered for further analysis. These criteria were as follows: (a) studies conducted within graduate education settings, (b) publications appearing in peer-reviewed

journals between 2013 and 2023, (c) articles written in English, and (d) alignment with the researchers' definition of HyFlex instruction. Conversely, exclusion criteria for this review included: (a) research conducted outside graduate education settings, (b) systematic reviews, meta-analyses, or conceptual papers, (c) studies set in contexts that did not adhere to the agreed-upon definition of HyFlex instruction, (d) unpublished manuscripts or works not appearing in peer-reviewed journals, and (e) peer-reviewed publications not written in English.

Procedure

The initial searches of the databases yielded 1,543 unique papers, after elimination of 355 duplicates. The 1,543 papers were uploaded to Covidence for review. Once in Covidence, the software identified an additional 29 duplicates, and 2 duplicates were identified by one of the research team members. These duplicates were removed, leaving 1,512 papers to screen. The first level of screening included reviewing titles and abstracts by at least one member of the research team. The review of titles and abstracts was conducted to determine whether each article met, potentially met, or did not meet the inclusion criteria. Articles were categorized as “yes,” “no,” or “maybe” based on this evaluation. A total of 287 were marked yes or maybe.

These 287 papers were further reviewed in a second level of screening involving a full text review by two members of the research team. Each paper was independently read by two researchers who voted either to *include* or *exclude* it from the systematic review. To reduce bias, the two researchers did not know how the others voted until all articles were reviewed. Once all articles were reviewed, the members of the research team met to discuss and resolve any conflicts. After the researchers reached agreement, 28 articles met the inclusion criteria for the systematic review.

Data Extraction and Coding

Nine elements were selected for analysis based on the research questions: (1) year of publication, (2) publication outlets, (3) number of authors, (4) geographical distribution, (5) subject-matter domains, (6) number of participants, (7) methodologies, (8) funding sources, (9) research questions, and (10) research outcomes. Based on these research elements, a data extraction form was created in Covidence. The data extraction form, in Covidence, allowed the research team to retrieve the research elements as reported in the journal articles. The initial data extraction was completed by one member of the research team. Afterwards, a second team member reviewed and approved all the data retrieved. After data was extracted from all 28 articles, the data collected was exported as an MS Excel spreadsheet for further coding and analysis. With all the data compiled in an MS Excel spreadsheet, information on (1) year of publication, (2) number of authors, (3) geographical distribution, (4) subject-matter domains, (5) number of participants, (6) methodologies, and (7) funding source was organized into separate tables according to each research element. These tables include the categories of research elements and the distribution of articles across each category. Subsequently, graphs were created to visually represent each research element.

The research outcomes were coded using a priori codes. The researchers developed a codebook based on the variables explored in the research questions extracted from the journal articles. The codes included: (a) perceived satisfaction, motivation, and success, (b) academic performance, (c) class attendance, (d) attentiveness, (e) interactions, (f) channels of interactions,

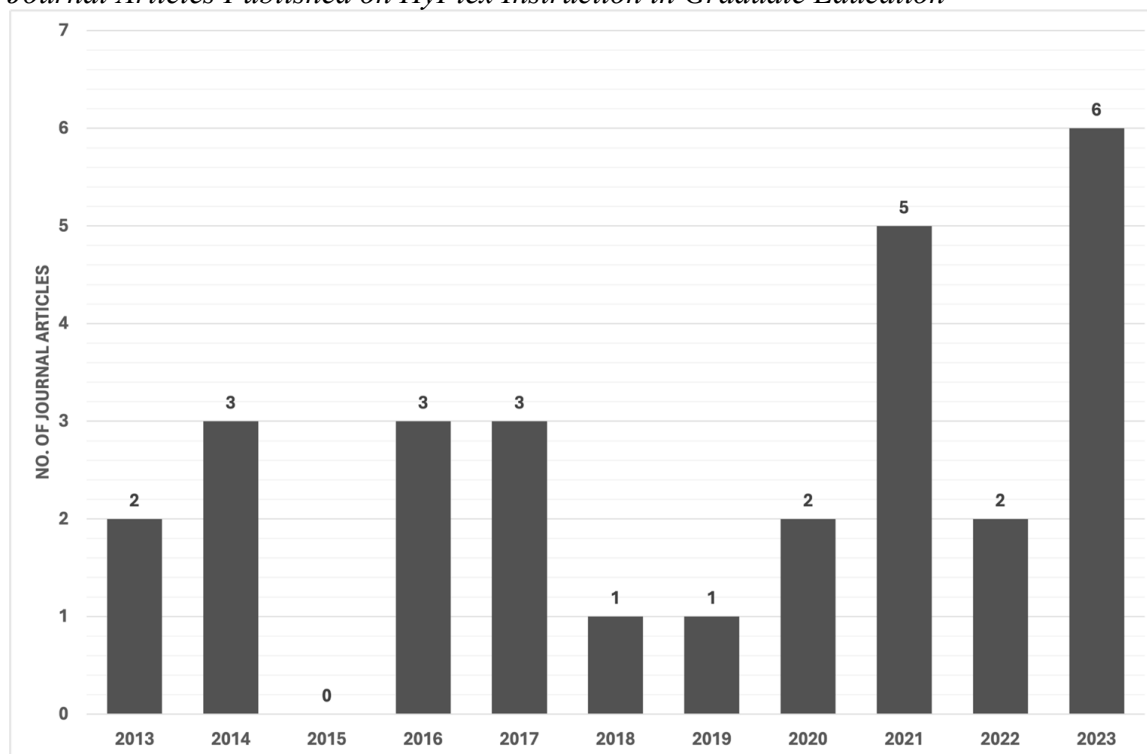
(g) robot-mediated learning, (h) benefits of HyFlex instruction, (i) challenges of HyFlex instruction, (j) technological design, (k) organization and logistics, (l) engagement, (m) dimensions of dialogue, (n) skills and attitudes, and (o) instructional design. Using an iterative coding approach, we systematically analyzed the outcomes of each journal article and related them to the pre-established codes. This process involved multiple rounds of coding to ensure consistency and accuracy. Each outcome was carefully examined to determine its alignment with one or more of the predefined codes. Discrepancies were discussed among the researchers until a consensus was reached.

Results

What were the main characteristics of the scientific literature on HyFlex learning in graduate education, considering factors such as (a) year of publication, (b) publication outlets, (c) number of authors, (d) geographical distribution, (e) subject-matter domains, and (f) number of participants?

Figure 2

Journal Articles Published on HyFlex Instruction in Graduate Education

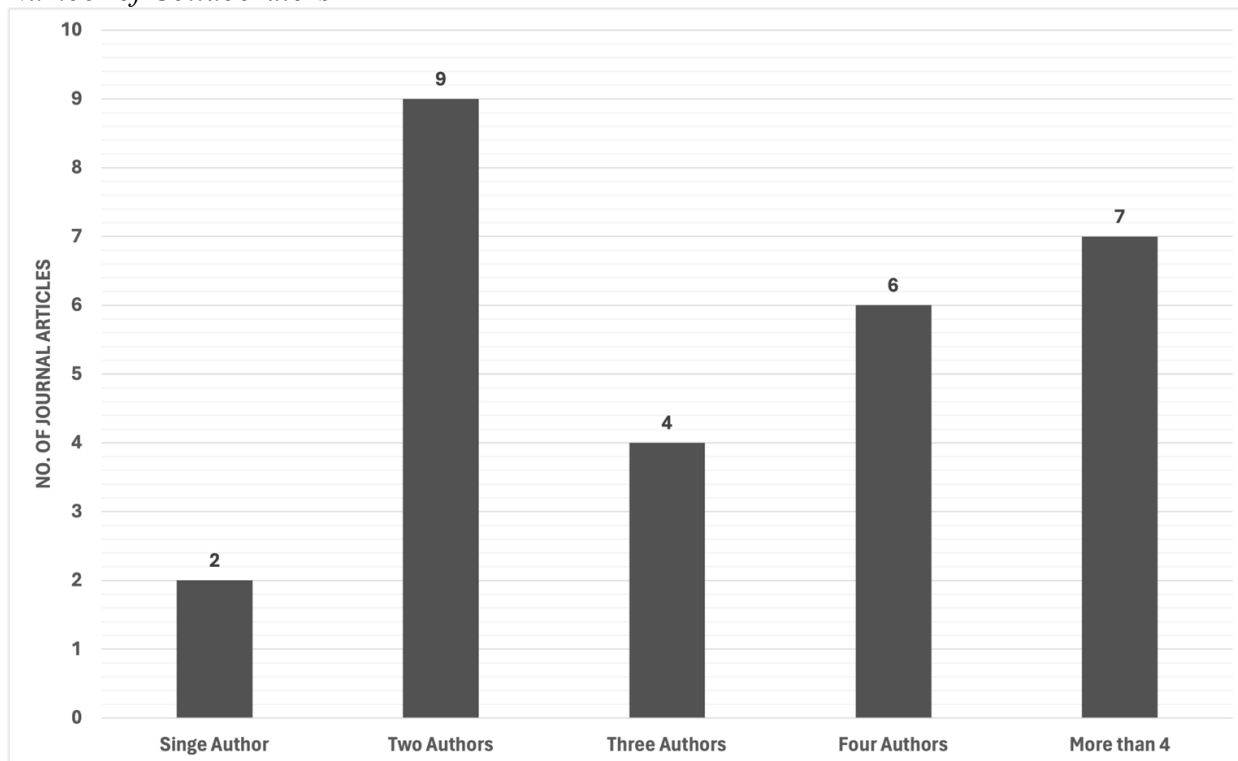


The systematic review of the literature on HyFlex instruction in graduate education revealed that 46% of the 28 journal articles included were published in the last three years of the review period. These results show a trend towards more research focusing on HyFlex instruction (see Figure 2), which could be attributed to the increased interest in online learning modalities due to the COVID-19 pandemic. The pandemic highlighted the importance of education frameworks that can quickly adapt to changing circumstances. This surge could also reflect the

urgent need for more flexible and adaptive learning models that can accommodate students in person and online simultaneously.

The journal articles that met the inclusion criteria were published in a range of different publication outlets. Most of the publication outlets focused on educational technology, learning design, and online learning research; however, a few were focused on other specific subjects such as hospitality, medical education, health research, and management education (see Table 1). This highlights that need for HyFlex instruction for teaching and learning in different disciplines. For instance, in medical education, HyFlex instruction can facilitate flexible learning schedules for students who may have clinical rotations or other commitments. In hospitality and management education, HyFlex models can support students who are balancing work and study. It reflects the growing recognition of HyFlex instruction as a valuable pedagogical approach.

As part of the analysis of the publications, the researchers categorized the journal articles based on the number of collaborators. The analysis revealed that research in HyFlex instruction in graduate education is a highly collaborative endeavor. As shown in Figure 3, 93% of the publications were co-authors by two or more researchers. Additionally, a cross-tabulation analysis between the years of publication and the number of authors for each publication included in the review showed that 2021 and 2023 were the years with the most collaborative research efforts focused on HyFlex instruction in graduate education.

Figure 3*Number of Collaborators***Table 1**

Journal Articles Focused on HyFlex Instruction in Graduate Education Published Between 2013 and 2023

Author(s)	Title	Journal
Angelone et al., 2020	Optimizing the technological design of a blended synchronous learning environment	Online Learning
Bell et al., 2016	From 2D to Kubi to Doubles: Designs for student telepresence in synchronous hybrid classrooms	International Journal of Designs for Learning
Butz et al., 2014	Motivation in synchronous hybrid graduate business programs: A self-determination approach to contrasting online and on-campus students	MERLOT Journal of Online Learning and Teaching
Butz & Askim-Lovseth, 2015	Oral communication skills assessment in a synchronous hybrid MBA programme: Does attending face-to-face matter for US and international students?	Assessment & Evaluation in Higher Education
Butz et al., 2016	The impact of emotions on student achievement in synchronous hybrid business and public	Decision Sciences Journal of Innovative Education

Author(s)	Title	Journal
	administration programs: A longitudinal test of control-value theory	
Chen, 2022	Designing online discussion for HyFlex learning	International Journal of Educational Methodology
Conklin et al., 2019	Graduate students' perceptions of interactions in a blended synchronous learning environment: A case study	The Quarterly Review of Distance Education
Cunningham, 2014	Teaching the disembodied: Othering and activity systems in a blended synchronous learning situation	The International Review of Research in Open and Distance Learning
Joanpere-Foraster et al., 2023	Dialogic teaching beyond words	Multidisciplinary Journal of Educational Research
Gleason & Greenhow, 2017	Hybrid learning in higher education: The potential of teaching and learning with robot-mediated communication	Online Learning
Hayes & Tucker, 2021	Using synchronous hybrid pedagogy to nurture a community of inquiry: Insights from a tourism master's programme	Journal of Hospitality, Leisure, Sport & Tourism Education
Heilporn & Lakhal, 2021	Converting a graduate-level course into a HyFlex modality: What are effective engagement strategies?	The International Journal of Management Education
Ho et al., 2023	Linking the choice of the class format and pre-class learning experiences sheds light on a step further in blended medical education	Medical Education Online
Howell et al., 2023	HyFlex pedagogy: Six strategies supported by design-based research	Journal of Applied Research in Higher Education
Kohnke & Moorhouse, 2021	Adopting HyFlex in higher education in response to COVID-19: Students' perspectives	Open Learning: The Journal of Open, Distance and eLearning
Lakhal et al., 2020	Features fostering academic and social integration in blended synchronous courses in graduate programs	International Journal of Educational Technology in Higher Education
Lakhal et al., 2021	Students and instructors' perspective on blended synchronous learning in a Canadian graduate program	Journal of Computer Assisted Learning
Macharaschwili & Coggin, 2013	A skype-buddy model for blended learning	Journal of Interactive Learning Research

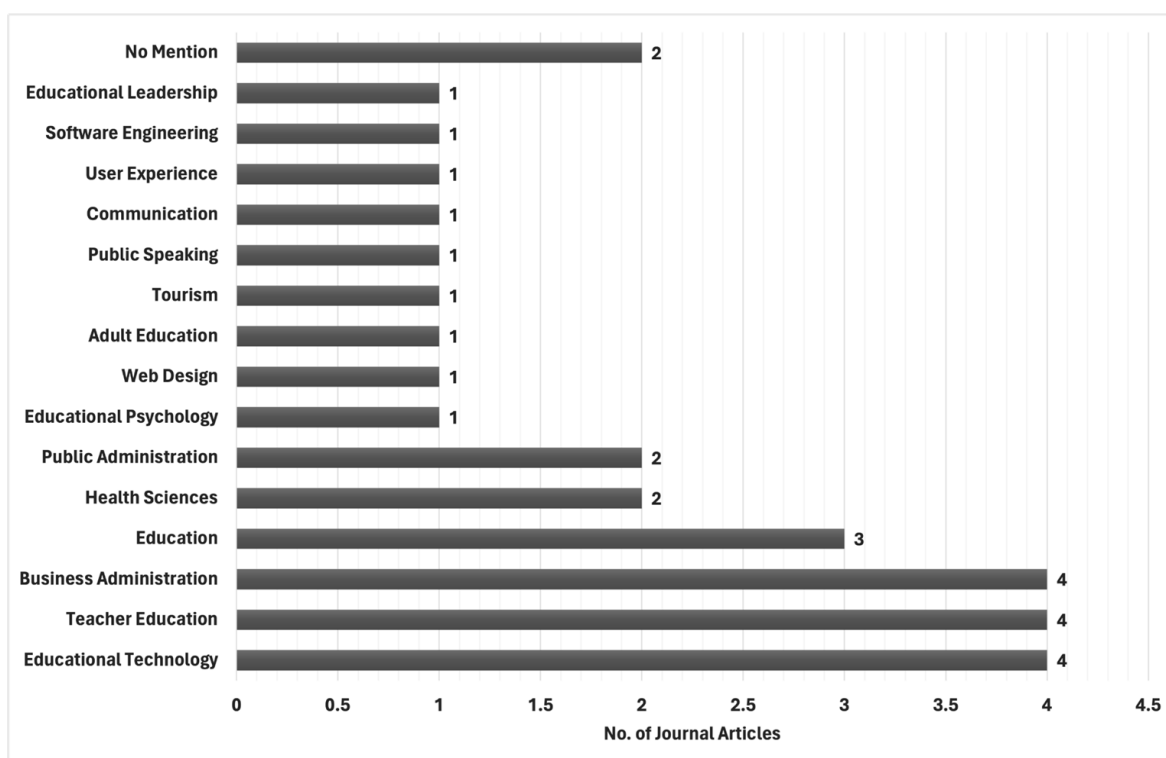
Author(s)	Title	Journal
Mccaw et al., 2023	From “Am I just too old for this?” to “Hey, I think I could do that!”: a collaborative self-study of the implementation of blended synchronous learning in initial teacher education	Education and Information Technologies
Nykvist et al., 2021	Key factors needed for developing a higher education cross-campus learning environment in a Nordic context	Frontiers in Education
Petchamé et al., 2023	Digital transformation in higher education: A qualitative evaluative study of a hybrid virtual format using a smart classroom system	Heliyon
Protsiv et al., 2016	Blended learning across universities in a South-North-South collaboration: a case study	Health Research Policy and Systems
Romero-Hall & Vicentini, 2017	Examining distance learners in a hybrid synchronous course: Successes and challenges	Online Learning
Smith et al., 2020	Are they paying attention, or are they shoe-shopping? Evidence from online learning	International Journal of Multidisciplinary Perspectives in Higher Education
Verdecchia & Lago, 2023	Tales of hybrid teaching in software engineering: Lessons learned and guidelines	IEEE Transactions on Education
Vu & Fadde, 2013	When to talk, when to chat: Student interactions in live virtual classrooms	Journal of Interactive Online Learning
Wang et al., 2017	Designing and improving a blended synchronous learning environment: An educational design research	International Review of Research in Open and Distributed Learning
Wang et al., 2018	Students’ perspectives on the design and implementation of a blended synchronous learning environment	Australasian Journal of Educational Technology

An analysis of the publications based on geographical location revealed that most of the research 43% ($n=12$) is being conducted in the United States. However, the analysis also revealed that research in HyFlex instruction in graduate education is being explored globally. Research in HyFlex instruction in graduate education was also conducted in Canada ($n=3$), New Zealand ($n=2$), Singapore ($n=2$), Uganda ($n=1$), Taiwan ($n=1$), Sweden ($n=1$), Spain ($n=1$), South Africa ($n=1$), Norway ($n=1$), Netherlands ($n=1$), China ($n=1$), and Australia ($n=1$).

Some of the research projects reported in the analyzed journal articles were conducted across multiple countries. Additionally, two publications did not specify the geographical location where the research was conducted. The international scope of the research suggests that there are shared opportunities and challenges implementing HyFlex instruction across different regions of the world. Moreover, it highlights the importance for researchers to consider cultural factors that may influence research outcomes.

Figure 4

Overview of All the Subjects Discussed in the Journal Articles

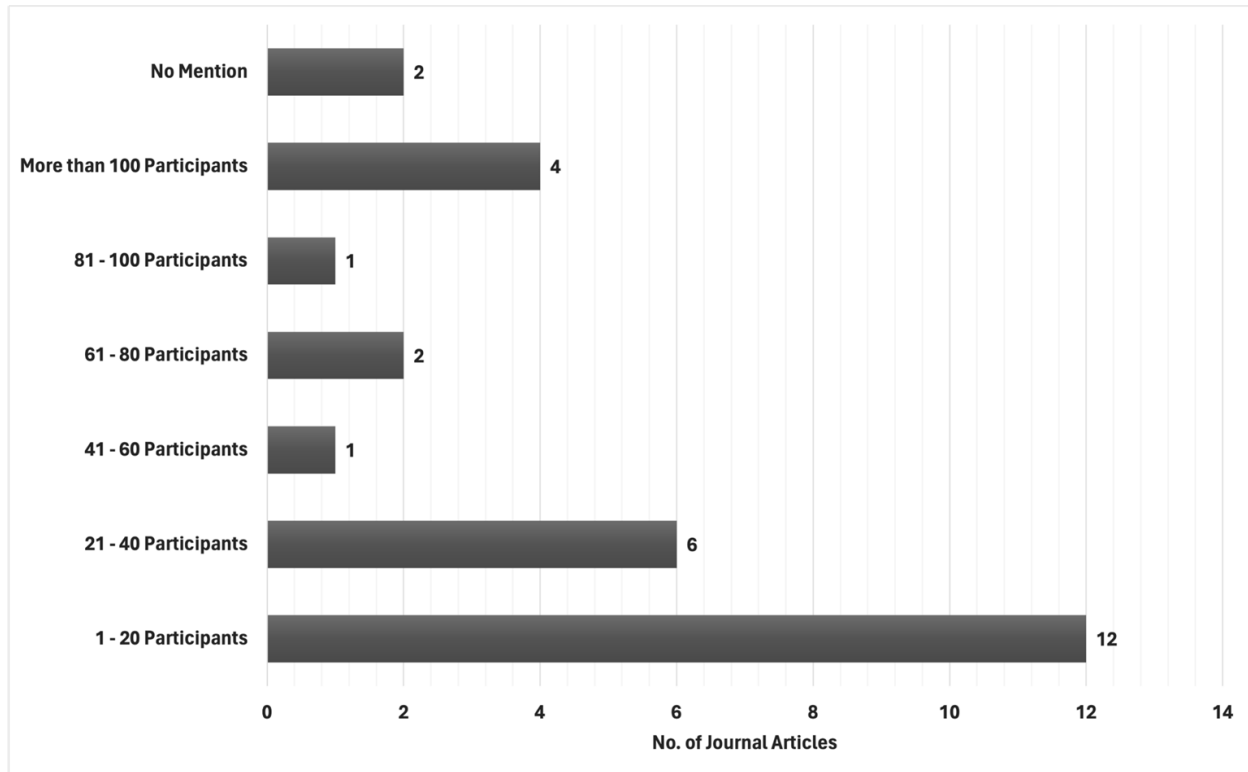


The journal articles included in the review conducted research in courses, programs, or degrees with a variety of subject-matters. Figure 4 provides an overview of all the subjects discussed in the journal articles. Teacher education (14%), business administration (14%), educational technology (14%), and education (11%) were the primary subjects in which HyFlex instructional modality was most often frequently implemented and researched. The two journal articles did not specify the subject-matter context in which the research occurred. These findings are connected to the diversity of journals in which this research is published, as noted earlier in this paper. Since the research spans various subjects, it is also disseminated through journal articles that cover topics beyond education and educational technology.

The journal article analysis also focused on the number of participants in each investigation published (see Figure 5). Six categories were created to classify each research project: (a) 1 – 20 participants, (b) 21 – 40 participants, (c) 41 – 60 participants, (d) 61 – 80 participants, (e) 81 – 100 participants, and (f) over 100 participants. The results of the analysis showed that in 43% of the journal articles there were 1 – 20 participants and in 20% of the journal articles there were 21 – 40 participants. Although four of the 28 studies were conducted with a sample size of over 100 participants, the results indicate that most of the research on HyFlex instruction in graduate education was conducted with a smaller sample size. Two of the journal articles did not report their sample size. This distribution suggests that while large-scale studies are valuable for generalizability, much of the current research relies on smaller sample sizes, which may offer more detailed insights but could limit broader applicability.

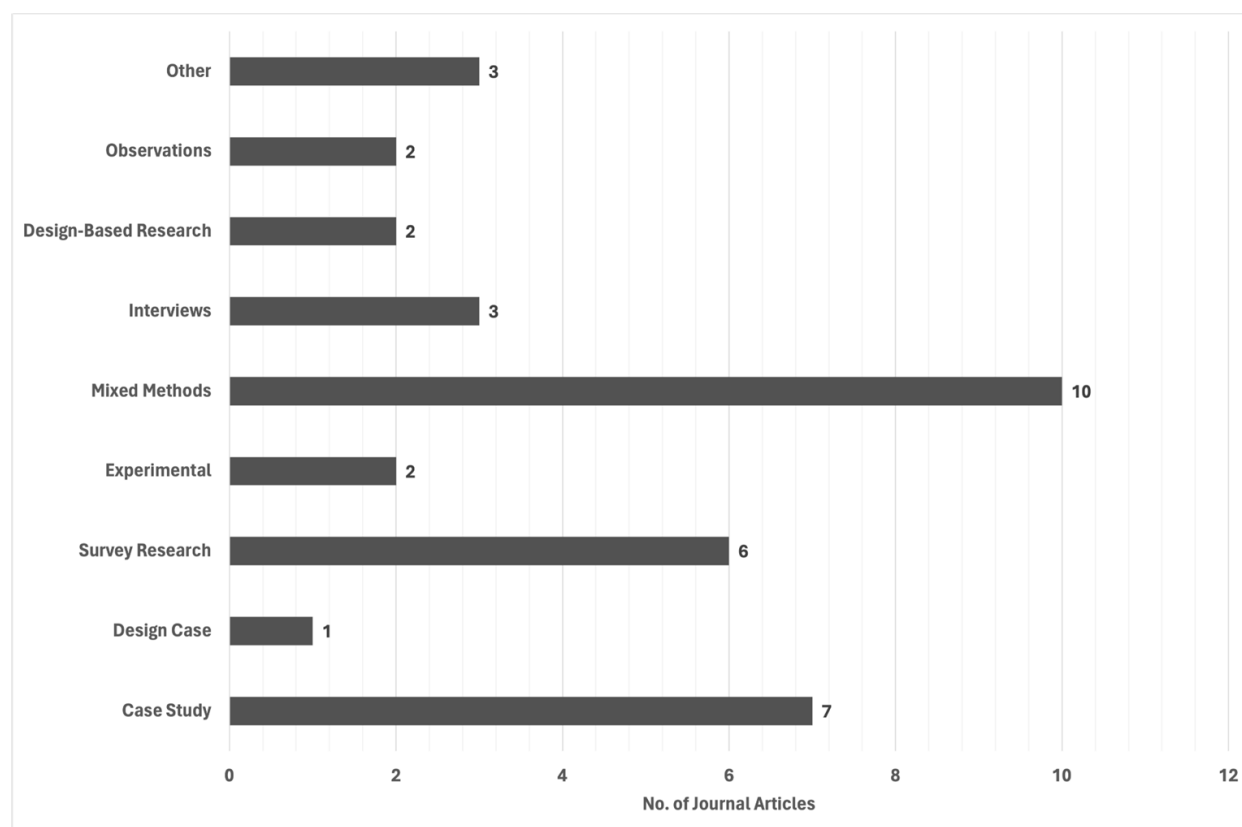
Figure 5

Number of Participants in the Investigations Published



What are the major research methodologies, funding sources, and research outcomes in studies of HyFlex learning in graduate education?

Another important trend that we wanted to explore in the literature included in this systematic review was the types of methodologies used by scholars to explore and research HyFlex instruction in graduate education. Some research projects used multiple methods of data collection. If multiple methods of data collection were acknowledged individually within the manuscript, then they were accounted for individually in the analysis. However, if the multiple methods were referred to as “mixed methods” in the journal article, then they were acknowledged within the “mixed methods” category. The results show that overall mixed methods ($n=10$) were the primary methodology used by researchers to investigate HyFlex instruction in graduate education. Case study ($n=7$) and survey research ($n=6$) methodology were also often used as a method of inquiry. Other methodologies mentioned less often included interviews, observations, experimental design, design-based research, and a design case (see Figure 6).

Figure 6*Types of Research Methods Used*

Of the 28 journal articles, 11 acknowledged receiving funding from an organization in support of the research conducted. Five journal articles received funding from government funding agencies (i.e., Social Sciences and Humanities Research Council of Canada, Ministère de l'Éducation et de l'Enseignement du Québec, European Union, and the National Science Foundation of China). The researchers in the remaining six journal articles disclosed receiving funding from institutional sponsors (i.e., California State University East Bay, University of Otago Teaching Development Grant, University of Melbourne Learning and Teaching Initiative Grant, Norwegian University of Science and Technology Teaching Excellence project SALTO, Challenges in University Teaching in the Post-COVID 19 Era at the Aristos Campus Mundus, and the Nanyang Technological University EdeX Teaching and Learning Project).

The research findings from the journal articles were analyzed to gain a comprehensive understanding of the key insights and conclusions drawn from the studies (see Table 2). The results highlight the complexity and multifaceted nature of HyFlex instruction in graduate education. The specific variables explored, and the corresponding outcomes reported in the journal articles included in this review are detailed below:

- **Perceived Satisfaction, Motivation, and Success:** Butz et al. (2014) explored differences in “need satisfaction” among students enrolled in synchronous hybrid

programs. Need satisfaction refers to the fulfillment of psychological needs for autonomy, competence, and relatedness—key drivers of intrinsic motivation. This intrinsic motivation plays a critical role in influencing students' persistence, creativity, and perceived success. The study revealed minimal differences between online and on-campus students in terms of need satisfaction, motivation, and perceived success. However, online students reported experiencing greater isolation, likely due to their focus on completing academic programs while managing work and family responsibilities, rather than seeking new social connections. Despite these challenges, both groups maintained high expectations for success in their courses. In a subsequent study, Butz et al. (2016) examined perceived success in relation to achievement emotions such as enjoyment, anxiety, and boredom. The findings indicated that while online and on-campus students experienced similar emotions, their levels of activation varied depending on the learning environments associated with their respective attendance modes. As anticipated, perceived success showed a positive correlation with enjoyment and a negative correlation with anxiety and boredom.

- **Academic Performance:** Butz & Askim-Lovseth (2015) found no significant differences in academic performance, including individual competencies and oral communication scores, between online and on-campus students in synchronous hybrid programs. Similarly, no differences were observed between domestic and international students. Chen (2022) also explored academic performance, focusing on non-text-based online discussions in HyFlex environments. The study revealed mixed results for task completion rates, with the highest rates observed in the initial sections of GoReact and Facebook classes, facilitated by their integration into Blackboard. Ho (2023) investigated short-term learning outcomes among medical students across different synchronous class formats (face-to-face, online, HyFlex), finding similar outcomes across all groups.
- **Class Attendance:** Verdecchia & Lago (2023) and Vu & Fadde (2013) both explored differences between online class attendance compared to in-person. Verdecchia & Lago noted that online attendance consistently exceeded in-person attendance, while Vu & Fadde observed a similar trend in Live Virtual Classrooms (LVC) across two semesters.
- **Attentiveness:** Smith (2020) explored the statistical difference between average attentiveness in courses in which all students participate via Zoom, compared with courses in which some students are in a physical classroom and some join via Zoom. Analysis showed that online courses where all the students as well as the instructor are logged on to Zoom synchronously had slightly statistically significantly higher average attentiveness compared to hybrid format courses where some students are physically in the classroom, and some are on Zoom.
- **Interactions:** Verdecchia & Lago (2023) observed differences in punctuality and engagement within a HyFlex classroom: In-person students arrived on time, whereas online students tended to join sporadically during the first 30 minutes. Web camera usage steadily decreased during lectures, with few remaining active until the end. Challenges in interaction were prominent, with many students struggling to engage effectively in class. Research in a blended synchronous learning environment (BSLE) found that although

students felt instructors distributed attention equally between online and in-person students, actual interaction data showed discrepancies (Conklin et al., 2019). Face-to-face students, who constituted 37% of the class, were responsible for most interactions with instructors, whereas online students, making up 63% of the class, only accounted for 25.7% of these interactions. Student-to-student engagement was among in-person students, revealing a gap in virtual connectivity.

- **Channels of Interactions:** In a study on HyFlex instruction, Vu & Fadde (2013) found that students preferred text interactions via chat (80%) over verbal interactions (20%) in Live Virtual Classrooms. Text interactions were comments (71%) and questions (29%), while verbal interactions included comments (88%) and questions (12%). Students were notably more inclined to use text for asking questions.
- **Robot-Mediated Learning (RML):** Gleason and Greenhow (2017) and Bell et al. (2016) investigated the role of robot-mediated learning (RML) in HyFlex classrooms, emphasizing its impact on embodiment and social presence. RML involves the use of mobile social robotic systems, such as Double and Kubi telepresence robots, to enhance the HyFlex learning experience. Students reported that RML improved engagement by facilitating recognition of addressed individuals and enabling observation of non-verbal cues, effectively simulating physical presence in the classroom. However, challenges were noted, including limited visibility and audibility for online students using the robots, particularly at a distance. Furthermore, successful implementation required instructors to actively coordinate interactions to bridge communication gaps between online and in-person participants.
- **Benefits of HyFlex Instruction:** Kohnke & Moorhouse (2021), Wang et al. (2018), and Petchamé et al. (2023) highlighted flexibility as a primary benefit of HyFlex and blended synchronous learning. Kohnke & Moorehouse noted that students valued the return to face-to-face classes after a semester of remote learning during the COVID-19 pandemic, appreciating the adaptability HyFlex provided. Similarly, Wang et al. and Protsiv et al., 2016's research emphasized that such flexibility allowed students to engage in lessons when unable to attend in person. This included enabling students to remotely attend classes from abroad (Petchamé et al., 2023). The three studies also pointed out that active involvement was crucial, with students taking initiative in their learning by communicating with peers and participating in classroom activities.
- **Challenges of HyFlex Instruction:** Research by Kohnke & Moorehouse (2020), Petchamé et al. (2023), and Romero-Hall & Vicentini (2017) identified several challenges of HyFlex instruction. One significant issue was the difficulties with handover and turn-taking, which impacted students' collaboration, progress monitoring, and feedback responsiveness. Additionally, students reported limited communication with face-to-face peers unless involved in team projects, highlighting the persistence of pre-existing relationships. Technical issues, such as inconsistent Internet connections, poor audio quality, issues framing the instructor through the camera, and not having the option of splitting the screen to have the view of multiple cameras, also adversely affected the

learning experience. In group settings, distance learners often felt undervalued and perceived unequal treatment compared to their face-to-face counterparts.

- **Technological Design:** Angelone et al. (2020) emphasized the critical role of technological design in enhancing blended synchronous learning environments, advocating for the selective integration of technologies that support effective pedagogy and foster co-presence among learners. Key recommendations include using technologies that allow constant visual connections, such as displaying online students' faces throughout the session, to promote a cohesive group feel. Additionally, creating separate breakout groups for online and on-campus students can facilitate direct communication and reduce frustration. Lakhal et al. (2021) further identified technological challenges, such as the need for ongoing training due to evolving technologies, the necessity of reliable technology and Internet connections, and how technological issues can disrupt participation and delay course sessions.
- **Organization and Logistics:** In terms of logistics and organization, students and faculty expressed that key factors are a) flexibility and accessibility, b) pairing of each instructor with a teaching assistant, c) adequate HyFlex room settings, and d) considerations for optimal group size (Lakhal et al., 2021).
- **Engagement:** Macharaschwili and Coggin (2013) investigated learner engagement with Skype in HyFlex instruction, revealing that chat functions were predominantly utilized to address technical issues and clarify classroom activities, while personal comments emerged as the second most common use. Academic discussions, however, were minimal. Despite this, both distance and in-person students expressed surprise at the meaningful personal connections formed during the course. Notably, technological issues did not impede these connections; rather, the day when the distance learner felt most disconnected was one marked by an absence of technical problems but minimal interaction with in-person students. Similarly, Cunningham (2014) and Hayes & Tucker (2021) found that online students valued being part of the class, hearing the instructor, and participating in discussions. However, online students often felt unwelcome by campus-based students. Feedback from campus students supported this perception, indicating some resentment toward the time and effort required to accommodate the technical needs of online learners (Cunningham, 2014). Additionally, there appeared to be a lack of understanding regarding how online students' mode of participation influenced their ability to interpret social cues (Hayes & Tucker, 2021).
- **Dimensions of Dialogue:** Joanpere-Foraster et al. (2023) explored the role of dimensions of dialogue in a HyFlex instructional setting. Results indicated that there are many communicative acts with mutual understanding but without agreement. The participants agreed that communicative acts were different from when they were online.
- **Skills and Attitudes:** Lakhal et al. (2020) identified key skills and attitudes for HyFlex instruction, recommending the following strategies: a) instructors with significant experience and a clear course vision ensure quality, regardless of the technology used; b) the instructor's attitude, openness, enthusiasm, and support are crucial for students'

academic and social integration; c) instructors' technological skills enhance online students' satisfaction and motivation; d) face-to-face students must recognize that online peers have different learning experiences; and e) online students should develop appropriate attitudes and technological skills to succeed.

- **Instructional Design:** A key area of HyFlex instruction research focuses on instructional design. Howell et al. (2023) outlined essential strategies for successful HyFlex course design, including: a) using chat as a backchannel for discussion, b) adopting a flipped classroom approach, c) using synchronous time for conferencing rather than whole-class instruction, d) scaffolding breakout room discussions with the 4A's protocol (assumptions, agreement, argument, aspirations), e) intentional student grouping, and f) optimizing classroom space, including camera and audio equipment. Mccaw et al. (2023) examined blended synchronous learning (BSL), revealing that despite educators' confidence in technology, implementation has proved more complex. Success was linked to co-teaching and technical support, with the most effective model involving a lead tutor and on-site BSL support who was also a subject tutor.

Nykvist et al. (2021) and Protsiv et al. (2016) explored factors essential to designing supportive learning experiences in HyFlex instruction, including the planning and variation of activities, digital tool selection for solving real-world problems, fostering student-teacher interaction, and prioritizing ownership of learning, collaborative and social learning experiences, prompt feedback (via email or during live sessions, or providing access to structure course materials). A focus on creating rich learning experiences using a pedagogy, space, and technology (PST) framework was emphasized. Wang et al. (2017) identified strategies for providing equivalent learning experiences for both classroom and online students, such as redesigning activities for online participation, balanced focus on online and classroom students and fostering communication through partnership strategies and ensuring clear video and voice communication. Wang et al. further noted that learning partnership strategies facilitated student engagement, enabling smoother participation. Technical training and sufficient classroom equipment, including multiple cameras and microphones, were also recommended.

Some journal articles examined supportive learning strategies in HyFlex instruction, as reported by graduate students. Heilporn & Lakhal (2021) found that course organization promoted continuous behavioral engagement, and recorded sessions enhanced cognitive engagement, with one student suggesting all sessions be recorded to support learning. Collaborative assignments, where students remained on the same team, boosted emotional engagement. Romero-Hall & Vicentini (2017) noted that distance learners felt more connected when other classmates were also remote, allowing for collaborative projects. Additionally, being online encouraged better study habits, with easy access to course materials and technology tools supporting their learning.

Table 2

Summary of Research Findings from the Journal Articles Included in the Systematic Review

Variables	Author(s)	Key Finding
Perceived Satisfaction, Motivation, and Success	Butz et al., 2014; Butz et al., 2016	Online and on-campus students exhibited minimal differences in need satisfaction, motivation, and perceived success. However, online students reported experiencing greater isolation, likely due to the challenges of balancing work and family responsibilities. Despite these differences, both groups maintained high expectations for success. However, perceived success was positively associated with enjoyment and negatively correlated with anxiety and boredom.
Academic Performance	Butz & Askim-Lovseth, 2015; Chen, 2022; Ho, 2023	There were no significant differences in academic performance between online and on-campus students. Research shows mixed results for task completion rates in HyFlex environments. Similarly, research show short-term learning outcomes across face-to-face, online, and HyFlex formats among medical students.
Class Attendance	Verdecchia & Lago, 2023; Vu & Fadde, 2013	Online attendance consistently exceeded in-person attendance. Research on Live Virtual Classrooms showed a similar trend over two semesters.
Attentiveness	Smith, 2020	Courses where all participants joined via Zoom synchronously had slightly higher average attentiveness compared to hybrid courses with mixed participation formats.
Interactions	Verdecchia & Lago, 2023; Conklin et al., 2019	In-person students were more punctual and engaged than online students. Discrepancies in instructor attention and student-to-student engagement were observed, with face-to-face students dominating interactions.
Channels of Interactions	Vu & Fadde, 2013	Students preferred text-based interactions (80%) over verbal interactions (20%) in Live Virtual Classrooms. Text was primarily used for comments and questions.
Robot-Mediated	Gleason & Greenhow, 2017; Bell et al., 2016	RML enhanced engagement by simulating physical

Variables	Author(s)	Key Finding
Learning (RML)		presence but faced challenges like (a) limited visibility and audibility for online students and (b) coordination demands on instructors.
Benefits of HyFlex Instruction	Kohnke & Moorhouse, 2021; Petchamé et al., 2023; Protsiv et al., 2016; Wang et al., 2018	Highlighted flexibility is a key benefit, allowing students to engage in lessons despite physical absence. However, active involvement of students is crucial for effective learning.
Challenges of HyFlex Instruction	Kohnke & Moorhouse, 2020; Petchamé et al., 2023; Romero-Hall & Vicentini, 2017	Identified issues like turn-taking difficulties, limited communication between online and face-to-face peers, technical problems, and unequal treatment of distance learners in group settings.
Technological Design	Angelone et al., 2020; Lakhal et al., 2021	Emphasized the importance of reliable technology, ongoing training, and tools that foster co-presence among learners. Recommended strategies include constant visual connections and separate breakout groups for online and on-campus students.
Organization and Logistics	Lakhal et al., 2021	Key organization and logistics factors included flexibility, accessibility, pairing instructors with teaching assistants, adequate HyFlex room settings, and optimal group size considerations.
Engagement	Macharaschwili & Coggin, 2013; Cunningham, 2014; Hayes & Tucker, 2021	Chat functions were primarily used to address technical issues and clarify activities rather than foster academic discussions. Despite limited academic engagement, personal connections developed between distance and in-person students. However, online students often felt unwelcome due to campus-based peers' resentment over accommodating their technical needs.
Dimensions of Dialogue	Joanpere-Foraster et al., 2023	Communicative acts often lacked agreement despite mutual understanding; significant differences existed between online and face-to-face communication dynamics.
Skills and Attitudes	Lakhal et al., 2020	Recommended strategies include experienced instructors with clear course vision, supportive attitudes from instructors, technological skills to enhance satisfaction and motivation, recognition of different learning experiences by face-to-face peers,

Variables	Author(s)	Key Finding
		and appropriate attitudes and skills from online students for success.
Instructional Design	Howell et al., 2023; Mccaw et al., 2023; Nykvist et al., 2021; Wang et al., 2017; Heilporn & Lakhal, 2021; Protsiv et al., 2016; Romero-Hall & Vicentini, 2017	Suggested strategies include using chat as a backchannel, flipped classrooms, scaffolding discussions with protocols like the 4A's, intentional grouping, optimizing classroom space/equipment, providing technical training, and fostering balanced communication between online/classroom students to ensure equivalent learning experiences.

Discussion

The purpose of this systematic review was to delineate key features of academic research related to HyFlex learning within the context of graduate education, specifically between 2013-2023. This included an analysis of the distribution of publications over time, the geographic distribution of research, and the number of collaborators. Secondly, the review aims to identify major research trends in terms of the subject matter domains explored, the methodologies employed, the number of participants in the research conducted, the funding sources, and outcomes observed in studies focused on HyFlex learning in graduate education. Through a synthesis of existing literature, we seek to offer insights into effective practices, identify areas for improvement, and foster dialogue around the evolving landscape of education in the digital age. This serves to inform educators, administrators, and researchers about the current state of the field and guide future directions for research and practice of HyFlex learning.

The research literature reviewed in this systematic study highlights that graduate students in HyFlex courses maintain high expectations for success, with no significant differences in academic performance observed between online and on-campus students. The findings also emphasize that graduate students demonstrate strong online attendance and attentiveness in HyFlex courses, while in-person students tend to be more punctual and exhibit higher levels of engagement. Challenges related to online student engagement are often attributed to technological issues, the absence of communication cues, and insufficient instructor facilitation mechanisms. Despite these obstacles, online students frequently leverage text-based communication channels to ask questions, share comments, clarify activities, and address technical difficulties. The literature underscores the importance of providing robust technological, organizational, logistical, and instructional design support to effectively implement HyFlex instruction in graduate education. Additionally, it recognizes the need for instructors to possess specific skills and dispositions tailored to teaching within this modality. Above all, graduate students favor HyFlex instruction for its flexibility and affordability, particularly because it eliminates the need for travel.

When comparing the findings of this systematic review to those from our previous review on undergraduate education (Romero-Hall et al., 2025), it is evident that the number of publications related to HyFlex instruction has remained relatively consistent for graduate

education. In contrast, studies focusing on HyFlex instruction in undergraduate education experienced a notable surge in publications during 2022 and 2023. Research on HyFlex instruction at both graduate and undergraduate levels reflects highly collaborative efforts, predominantly conducted in the United States, with additional studies representing diverse global contexts across various subject areas. Systematic reviews comparing HyFlex research between undergraduate and graduate students reveal distinct differences: Most undergraduate-focused studies involved more than 100 participants, whereas graduate-focused research typically included smaller sample sizes of 1–20 participants. Furthermore, while survey research was the primary methodology employed in undergraduate HyFlex studies, mixed methods approaches were more commonly used in research on graduate-level HyFlex courses.

In terms of research outcomes, studies on HyFlex instruction at the graduate and undergraduate levels reveal distinct areas of focus. At the graduate level, research emphasizes questions such as “How should graduate HyFlex courses be designed?” addressing aspects like technology, instructional design, logistics, and instructor predisposition, as well as, exploring “What are the experiences of graduate students in HyFlex learning environments?” Conversely, research on HyFlex instruction at the undergraduate level also investigates “How should undergraduate HyFlex be designed?” and “What are the experiences of undergraduate students in HyFlex settings?” Additionally, undergraduate-focused studies often explore how to better prepare students for positive and successful learning experiences within HyFlex courses (Romero-Hall et al., 2025).

Limitations

While this systematic review offers valuable insights into the research related to the implementation and outcomes of HyFlex instruction in graduate education, it is essential to acknowledge certain limitations to contextualize the findings and their applicability. This systematic review focuses on research published in five specific databases within a defined timeframe, which may not encompass all existing studies on HyFlex learning in graduate education. Additionally, journal articles not published in English were excluded, limiting the representation of literature available in other languages. Furthermore, the search strategy did not account for grey literature (e.g., conference papers, dissertations, or proceedings), potentially omitting some relevant studies.

Identified Gaps and Future Research

Despite the increasing research on HyFlex teaching in graduate education, several gaps remain that warrant further exploration. First, there is a notable lack of longitudinal studies examining the long-term impacts of HyFlex teaching. While much of the current literature focuses on short-term outcomes like student satisfaction and immediate academic performance (Butz, 2014; Ho et al., 2023), few studies have explored how HyFlex impacts students’ long-term progress, retention, and overall academic success. Further research is needed to assess whether HyFlex models truly support sustained academic achievement, particularly for students balancing coursework with professional and personal responsibilities. This is especially important in graduate programs, where students often juggle various life commitments. Understanding how these learners navigate the demands of HyFlex over the course of their entire program can provide insight into whether this model meets the long-term educational needs of diverse student populations.

Additionally, the integration of technology in HyFlex environments remains an underexplored area. Although studies have mentioned challenges related to technological infrastructure (Lakhal et al., 2021), few have examined how to design more inclusive and equitable digital environments. These environments should support both online and in-person learners equally, ensuring that students in both modalities have access to comparable learning experiences and resources (Wang et al., 2018). For instance, while technological tools such as learning management systems and video conferencing platforms are integral to HyFlex classrooms, the effectiveness of these tools in creating an engaging and interactive learning experience for both online and in-person students have not been sufficiently examined. Further research should investigate how these technologies can be optimized to promote engagement, interaction, and equity across learning modalities. Additionally, the role of emerging technologies like virtual and augmented reality, which have the potential to bridge the gap between online and in-person learners, remains a critical area for future study.

Moreover, further investigation is required to understand the dynamics of interaction and engagement between online and in-person students. Studies indicate that there are often differences in interactions between these two groups, with distance learners frequently feeling undervalued and perceiving themselves as treated unequally (Romero-Hall & Vicentini, 2017; Kohnke & Moorhouse, 2020). Research should focus on developing strategies to foster stronger engagement and collaboration across modalities, such as structured group activities or peer mentoring programs, to enhance integration between online and face-to-face students (Howell et al., 2023; Wang et al., 2018). Additionally, it is essential to explore the psychological and social factors that may lead to feelings of isolation among online learners and how intentional course design and instructional support can help alleviate these challenges.

The systematic review underscores a pressing need for more empirical research on faculty attitudes toward HyFlex instruction. As demonstrated in this review, the adoption of HyFlex instruction has grown significantly since 2020, providing ample opportunity for faculty to experiment with and adapt to this learning modality. Understanding faculty perspectives through robust empirical evidence would not only enrich graduate education but also offer valuable insights for institutional leaders and educators across all levels of academia. Such research could inform the development of targeted support systems, resources, and strategies to enhance the effectiveness and sustainability of HyFlex instruction.

Although HyFlex teaching gained prominence during the COVID-19 pandemic, there is still a need for deeper research into its relevance in the post-pandemic landscape. As the immediate demand for flexible learning decreases, it is crucial to explore how HyFlex can continue to meet the evolving needs of graduate students, especially those with geographic or professional constraints (Kohnke & Moorhouse, 2021). While many students benefited from the flexibility HyFlex offered during the pandemic, the shift of higher education institutions back toward more traditional models highlights a critical need to evaluate whether HyFlex can sustain institutional support and student interest in this new context. Future research should focus on how the model can be adapted to align with shifting educational priorities and rising student expectations. Addressing these gaps will be essential for ensuring the continued efficacy and scalability of the HyFlex model in higher education.

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The authors declare no conflicts of interest related to the research, authorship, or publication of this article.

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“I Get It Now”: Insights from Implementing Metacognitive Strategy Instruction Through an Asynchronous Gradual Release of Responsibility Framework

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Abstract

This study explores the impact of explicit metacognitive instruction delivered through the Gradual Release of Responsibility framework on graduate students’ metacognitive moves while reading. Conducted over multiple iterations, the research examines how explicit instruction in metacognitive strategies affects students’ engagement with academic texts through asynchronous social annotation using iterative thematic coding. Findings from the latest iteration indicate that while the Gradual Release of Responsibility framework supports more varied and strategic reading behaviors, factors such as text complexity and instructional approach significantly influence students’ application of these strategies. For instance, graduate students in a digital literacies course demonstrated a greater use of questioning and critical reflection compared to their peers in a phonics-focused course, where monitoring was the predominant strategy. Despite explicit instruction, results across all iterations underscore three ongoing challenges: (1) even graduate students may not inherently possess strong metacognitive reading skills, (2) isolated metacognitive instruction in one course is insufficient for long-term development, and (3) students exercise significant agency in choosing how they engage with texts. These findings suggest the need for sustained cross-curricular integration of metacognitive instruction to foster reflective, adaptable readers. This study supports a deeper understanding of metacognitive strategy development in graduate education, raising important implications for instructional design and teacher preparation.

Keywords: Metacognitive strategies, gradual release of responsibility, social annotation, graduate education, instructional design

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As teacher educators, it is our aim to prepare teachers who not only read about effective comprehension pedagogies but ensure that our candidates have the metacognitive comprehension moves to serve as good models for their students. We take a cognitive constructivist view of comprehension in which the reader actively constructs meaning by going beyond linking background knowledge to monitor the development of meaning and use strategies and “metacognitive insights” to assure that meaning is being built (Dewitz & Graves, 2021, p. S132). We sought to examine the metacognitive moves through a series of student case studies to compare strategies of Literacy Master’s of Education (MSED) students.

This study examines the efficacy of an asynchronous Gradual Release of Responsibility (GRR) framework in improving graduate students’ metacognitive moves when reading and annotating assigned course texts. Metacognitive moves provide insight into how readers manage and interpret text while engaging with learning materials. Understanding these moves is critical, as they reveal the ways in which students comprehend and engage with academic content. This research represents the fourth phase in an ongoing exploration of how graduate students interact with academic texts through social annotation.

Social annotation involves multiple students reading and commenting on a shared digital text file, a process that facilitates both individual reflection and group discourse (Glover et al., 2007). Tools like Perusall, which we used in this study, allow for access to the same text and enable asynchronous interactions among users. As constructivist educators, we value how social annotation frames literacy as a social activity, highlighting the collective interpretation of texts. In particular, we are interested in what social annotation reveals about users’ metacognitive and reading comprehension moves. By observing how students annotate, we can gain valuable insights into their interpretations and approaches to the texts.

Our initial research within a previous iteration (Adams et al., 2023; see Table 2 in Methods) was confined to a single program at one institution in the northeastern U.S., where we found that annotations by certified teachers studying literacy education were largely focused on text-to-self connections. However, moves such as synthesis and critique, both more complex strategies, were less frequent. These findings prompted us to replicate the study across different institutions and programs within our research group with iterations two and three, with the number of participating institutions and programs differing each time, to verify whether our observations held true in other settings. We found in iteration two (Wilson et al., 2024; see Table 2 in Methods), a cross-comparison of five institutions, that student annotations rarely demonstrated the types of metacognitive strategies identified as essential for comprehension. For example, Dewitz and Graves (2021) explain that effective readers engage in active meaning-making by setting purposes, asking questions, making inferences, monitoring understanding, and synthesizing ideas. However, our data revealed that students were not consistently enacting these behaviors. Instead, annotations often focused on surface-level reactions or personal connections, with limited evidence of inferencing, purposeful questioning, or summarizing. This discrepancy suggests that even graduate students have difficulty independently applying the full range of metacognitive strategies needed for deeper comprehension (Lei et al., 2010), a pattern that challenged our assumptions and informed the design of our later, more explicit instructional interventions. In response (iteration 3; Stevens et al., 2025), we refined our intervention to provide more explicit and systematic instruction in metacognitive moves, specifically tailored to

reading comprehension, through an asynchronous GRR framework deployed at two universities (see Table 2 in Methods). This paper evaluates the effectiveness of this enhanced intervention.

Literature Review

Metacognitive reading comprehension strategies are essential for students navigating complex academic texts, particularly at the graduate level. This review explores the theoretical foundations and instructional practices that inform the development of these strategies, with a specific focus on the GRR framework. By examining the role of metacognition, reading comprehension strategies, and the role of the teacher in explicit instruction, this section highlights key insights from prior research that inform the present study. Additionally, social annotation fosters collaborative and reflective reading practices (Adams & Wilson, 2020), offering a lens through which we can observe real-time metacognitive engagement. These insights form the foundation for evaluating how our asynchronous GRR intervention impacts graduate students' reading comprehension and metacognitive development.

Reading Comprehension and Metacognition

Reading comprehension is a complex cognitive process that involves internal mental activities, making it challenging to assess and instruct effectively (Pearson & Cervetti, 2017; Adams et al., 2023). At the core of this study is the premise that readers actively construct meaning through metacognitive strategies. Metacognition, defined by Flavell (1979) as the awareness and control of one's cognitive processes, plays a crucial role in enhancing comprehension. It enables readers to engage in practices such as questioning, making inferences, and monitoring their understanding during the reading process (Duke et al., 2011). Metacognitive strategies are the hallmark of proactive learners who can effectively manage their own learning (Ward & Butler, 2019; Young & Fry, 2008).

Despite the recognized importance of metacognition, research has shown that students exhibit varying levels of metacognitive awareness (Karpicke et al., 2009; Ku & Ho, 2010). Some students demonstrate effective management of their learning across contexts, while others may not yet demonstrate self-awareness and regulation during reading (Young & Fry, 2008). Key comprehension strategies, such as questioning, activating prior knowledge, and monitoring comprehension (Duke et al., 2011; National Reading Panel, 2000; Ness & Kenny, 2016) are essential for extracting meaning from texts. Strategic readers adjust their approaches according to the demands of the text and the task (Almasi & Fullerton, 2012), while also recognizing and addressing comprehension breakdowns (Artis, 2008; Thomas & Barksdale-Ladd, 2000; White, 2004). Recent research has called into question the assumption that US graduate students inherently possess strong metacognitive and reading comprehension skills (Adams et al., 2023; Wilson et al., 2024; Lei et al., 2010). It is worth noting that during the time the students in the study received direct instruction in reading comprehension, students more than likely did not experience cumulative literacy learning with differentiation between skills and strategies (Dewitz & Graves, 2021). While it is beyond the scope of this study to analyze how their past reading instruction plays into how graduate students in the MSSED program teach literacy, it may have shaped how they engage with text.

Monitoring comprehension is central to the metacognitive reading process. It allows students to evaluate their understanding (e.g., complete, partial, or incomplete) and identify

strategies to resolve any gaps in comprehension (Baker, 1979; Soto et al., 2023). This process of self-regulation is key to successful reading, as students learn to recognize comprehension failures and apply appropriate strategies to improve their understanding (Soto et al., 2023).

Prior knowledge, or the information a reader brings from previous experiences, also plays a critical role in reading comprehension (Hattan, 2024). This type of knowledge includes concepts, experiences, and text structures (Brody, 2001), enhances comprehension by enabling readers to make connections and ask relevant questions during reading (e.g., Gaultney, 1995; Recht & Leslie, 1988; Tarchi, 2010). Without sufficient background knowledge, readers may have difficulty with comprehension and be less aware of the gaps in their understanding (Kendeou et al., 2019; Neuman, 2019).

Research indicates that when students have explicit instruction focused on metacognitive and comprehension strategies that are integrated into learning, students' reading improves (Dewitz & Graves, 2021). Instructors are encouraged to integrate explicit metacognitive instruction into their teaching practices to support students' comprehension development (Jiang et al., 2016; Zohar & Lustov, 2018). Ultimately, metacognitive strategies are invaluable in promoting reading comprehension, as they provide students with the tools to monitor their engagement with texts. By revealing how students apply knowledge, monitor their understanding, and self-regulate, social annotation provides critical data on their reading practices (Pintrich, 2000).

Role of the Teacher in Explicit Instruction and Building Metacognition

Duke and colleagues (2011) describe students learning to read effectively as a journey, where teachers serve as guides, helping students to stay on course, pausing to appreciate the landscape of understanding, and inviting some detours down interesting byways. Teachers play a pivotal role in explicit comprehension instruction and building students' metacognition. As such, teachers must be prepared to be proficient and flexible (Williams & Atkins, 2009) when it comes to comprehension instruction, specifically teaching comprehension strategies, within the GRR framework (Duke et al., 2011, 2021; Pearson & Gallagher, 1983).

It is well established in the literature that teachers matter when it comes to building students' comprehension (e.g., Snow et al., 1991; Taylor et al., 2003; Tivnan & Hemphill, 2005). Snow and colleagues (1991) found students made more progress in reading when they had strong teachers of reading comprehension. This finding also applies to explicit comprehension strategy instruction. The National Reading Panel (2000) report concluded that strategy instruction, where teachers and students interact over text, was highly successful. More recently, Mahdavi and Tensfeldt (2013) reported positive effects of comprehension strategy instruction in the primary grades. Okkinga et al. (2018) later concluded multiple-strategy instruction was effective in grades 3-12. Duke and colleagues (2021) stated, "Many benefit from explicit instruction in how to think before, during, and after reading; how to monitor their understanding; and how to help themselves when meaning breaks down" (p. 667). Overall, explicit strategy instruction from teachers who are highly knowledgeable is supportive of students' learning as they read.

Effective teachers of reading comprehension guide their students on the journey as they develop into metacognitive readers by teaching them why, how, and when to apply strategies (Duke & Pearson, 2002). It is recommended (Duke et al., 2011) that teachers teach

comprehension strategies through a GRR framework (Pearson & Gallagher, 1983). The historical and conceptual genesis of GRR (Pearson et al., 2019) was a result of Durkin's (1978) study which found little reading comprehension instruction was occurring in classrooms; rather, students were completing assignments such as question-response activities without developing comprehension skills. Since its genesis, GRR is a framework utilized across disciplines.

Gradual Release of Responsibility

There are six stages of GRR (Baumann & Schmitt, 1986; Duke et al., 2011; Pearson & Gallagher, 1983; Pearson et al., 2019; see Table 1). The first stage includes explicit description, where the teacher directly teaches what, how, when, and why to use the strategy. Second is the teacher-modeling stage where the teacher walks students through the strategy using a think-aloud or explicit instruction. During a think-aloud, teachers demonstrate or model their thinking or application of strategies (Duke & Pearson, 2002). Modeling makes the thinking process visible, showing students how to be strategic, metacognitive readers (McKeown & Beck, 2009). Third is collaborative use. In this stage, the teacher invites students to collaboratively use the strategy in action. Fourth is the guided practice stage where the teacher facilitates students' interactions with the text as they apply what they learned with gradual release of responsibility. Duke and colleagues (2011) emphasized the importance of the middle stages (collaborative use and guided practice) because teachers can provide explicit instruction and then inadvertently release responsibility before students are ready to practice independently. Fifth is the independent use stage, where students are tasked to use the strategy on their own. Sixth is reflection, when the teacher and students reflect on their performance to decide the next steps for instruction. Pearson and colleagues (2019) recently identified reflection as an essential phase of GRR, for both teachers and students.

Table 1

Stages of GRR (Pearson et al., 2019)

Stage	Description	Teacher's Role	Student's Role
1. Explicit Description	The teacher explicitly describes the skill or strategy.	Explains when and how it should be used.	Observes and listens to the teacher's explanation.
2. Teacher Modeling	The teacher demonstrates or models application of the skill or strategy	Models thinking aloud, shows the skill or strategy in action.	Observes and listens to the teacher's modeling or demonstration.
3. Collaborative Use	Students work together with teacher and peer support.	Reminds students of skill or strategy modeled and invites students to try it in action. Facilitates discussion, encourages peer interactions.	Tries skill or strategy with the support of others. Engages in discussions, shares ideas, and supports peers.

4. Guided Practice	The teacher guides students through practice with support.	Provides prompts, scaffolds learning, and gives feedback.	Participates, asks questions, and practices with assistance.
5. Independent Use	Students apply the skill or strategy on their own.	Observes, provides minimal guidance, and assesses learning.	Practices independently, applies knowledge, and self-monitors.
6. Application & Reflection	Students transfer learning to new contexts and reflect.	Encourages application to real-world tasks and metacognition.	Applies learning in novel situations and reflects on understanding.

Despite the list of stages above, GRR is both a nonlinear and recursive framework. Teachers and students may move through the stages of GRR in a nonlinear way. For instance, if teachers teach a unit of inquiry from a constructivist lens, they may have the students participate in independent use or guided practice before providing explicit instruction or modeling (Pearson et al., 2019). The non-linear nature of GRR is also important as teachers consider increasingly complex tasks, texts, and learning contexts (Webb et al., 2019). Teachers and students can “move back and forth between each of the components as they master skills, strategies, and standards” (Fisher, 2008, p. 2). Students may reach the fifth stage, independence, with a strategy and cycle back to stage one, two, three, or four needing explicit instruction, modeling, collaborative use, or guided practice depending on the complexity associated with the text. The duration of the steps may vary as some students may need more modeling or guided practice.

For teachers to be skillful and strategic in their instruction, they need a strong understanding of metacognition and the strategies and frameworks that support their teaching of metacognitive students (Williams & Atkins, 2009). Wilson and Bai (2010) found teachers’ understanding of metacognition was related to the strategies they understood to be effective in supporting students’ metacognition. Williams and Atkins (2009) asserted, “Only when teachers are aware of what their own comprehension entails will they be able to monitor their students’ reading and provide the right instruction for them” (p. 40). As such, scholars call for building teachers’ understanding of metacognition and reading comprehension, in coursework and professional development opportunities (Williams & Atkins, 2009; Wilson & Bai, 2010). This study seeks to uncover if the addition of explicit instruction using the GRR framework supported strategic reading through the application of varied metacognitive comprehension strategies.

Methods

This case study is part of an ongoing project, now in its fourth iteration, which explores how graduate students engage with academic texts through social annotation. Social annotation tools like Perusall allow students to read and annotate texts asynchronously, promoting collaborative meaning-making (Glover et al., 2007). While earlier iterations focused on students’ metacognitive behaviors, the current study seeks to understand how explicit instruction within the GRR framework supports metacognitive comprehension through strategic reading. The goal of each iteration is to further understand the quintain (Stake, 2006) to guide future research.

This case study utilizes grounded theory (Glaser & Strauss, 1967) to understand the nature of students' responses to readings with and without explicit instruction using the gradual release of responsibility model. The theory has been developing throughout each iteration of the study. Early iterations focused on creation of the code book. Later iterations worked with the code book to determine if there are variables that impact students' interactions with text. In this iteration the variable was explicit instruction in reading comprehension strategies using the gradual release of responsibility model. Previous iterations assumed strategy usage (Adams et al., 2023), provided implicit strategy instruction (Wilson et al., 2024), and provided explicit one time strategy instruction (Stevens et al., 2025).

Table 2

Previous Iterations

Iteration	Goals of the Study	Number of Institutions	Location of Institutions	Number of Participants Evaluated
1 (2022)	Learn about Metacognitive and social practices during reading	1 course	Northeast	12 students
2 (2023)	Learn about the comprehension and metacognitive practices novice teachers use through social annotation	1 (1 course)	Northeast	3 students
3 (2024)	Compare the comprehension and metacognitive strategies observed through social annotation, at different institutions	5 (6 courses)	Northeast (3) Northwest (1) Midwest (1) South (1)	18 students
4 (2025)	Evaluate how direct instruction in metacognitive strategy use for social annotation through Gradual Release of Responsibility support student comprehension	2 (2 courses)	Northeast	2 instructors

The primary tool for data collection for this study was Perusall, which is an online social annotation tool. Readings are uploaded to the tool and students work asynchronously to engage with text through the online platform. Unlike reading an electronic text (e.g., eBook, PDF file) independently, Perusall allows for readers to interact. For instance, if one reader clarifies the definition of a word used in the article, other readers can see the comment clarifying the definition. Perusall has been used for each iteration of this work. When completing assigned readings, students exercise agency in how closely they choose to read and when they choose to comment on what they read. Though there are expectations to demonstrate close reading, what that means is determined by the individual. Previously, studies in the project revealed that graduate students primarily engaged in text-to-self connections while annotating texts, even after additional instruction on metacognitive moves (Adams & Wilson, 2022; Adams, et. al, 2023;

Wilson, et. al. 2024). The consistency of these findings across institutions prompted the introduction of explicit, guided instruction following the similar procedures and slide deck in the current iteration. This phase builds on prior findings by using the GRR framework in an effort to scaffold students' metacognitive reading strategies, such as questioning and synthesizing information, while reading academic texts (Pearson & Gallagher, 1983).

Instructional Design

The instructional design for this study was developed within the GRR framework, which structures learning around six stages: explicit description, teacher modeling, collaborative use, guided practice, independent use, and reflection (Pearson & Gallagher, 1983; Pearson et al., 2019). This design-based approach aimed to scaffold graduate students' metacognitive reading skills by providing systematic, structured support at each stage of the learning process.

To foster metacognitive comprehension and strategic reading, the design incorporated social annotation through Perusall. The integration of social annotation into the GRR framework was grounded in constructivist principles, emphasizing that learning is a social process, especially when engaging with complex academic texts (Vygotsky, 1978; Glover et al., 2007). By designing activities where students could apply strategies like questioning, summarizing, and making connections in a collaborative online environment, the intervention sought to promote both individual metacognitive growth and collective meaning-making.

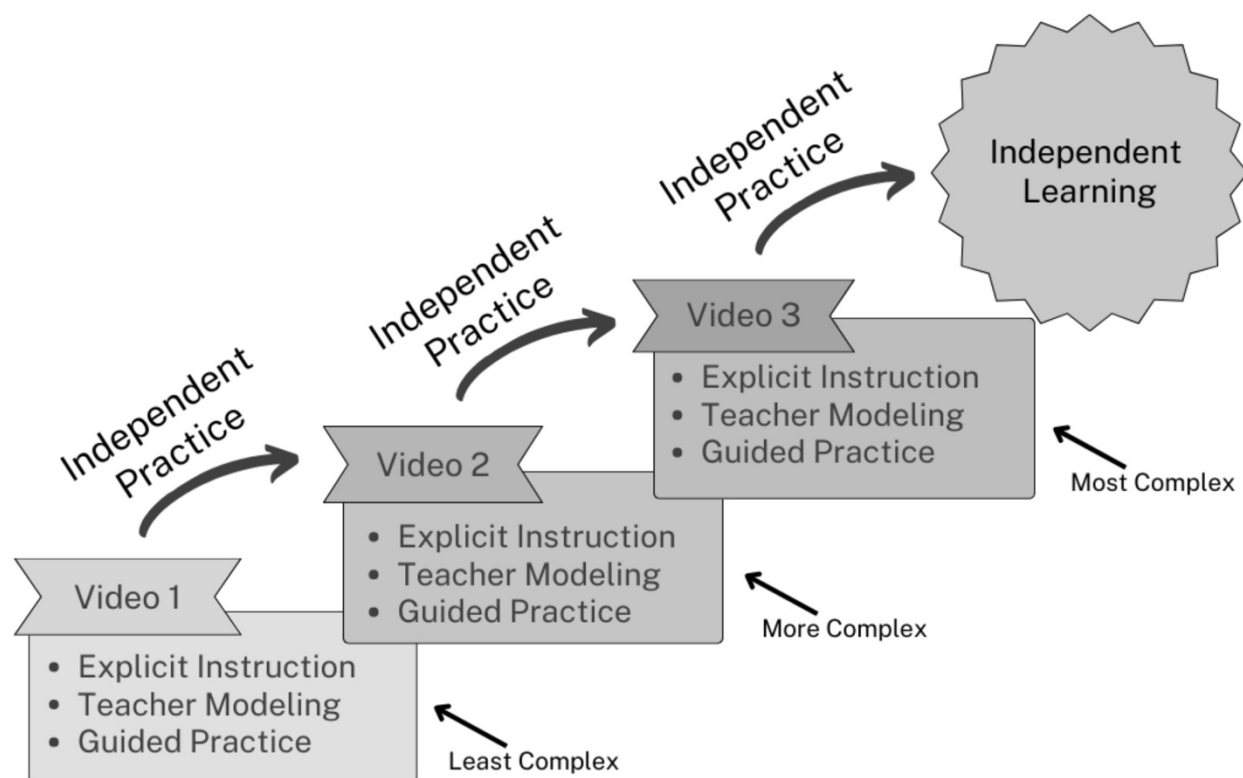
In alignment with the principles of design-based research, the instructional design was iterative, evolving through multiple cycles of refinement based on data from previous iterations (Reinking & Bradley, 2008). The approach was designed to be flexible, allowing for adaptation based on contextual needs, such as the course content, institutional setting, and the specific backgrounds of the graduate students. Instructors from two institutions, Wilson and Stevens, collaborated to align their course materials and deliver instruction that adhered to the GRR framework. It was determined that these institutions would be the focal points for this iteration as both instructors were working with students new to Perusall that semester, both were teaching asynchronous classes, and both were teaching content required by Literacy Master's degrees.

The explicit instruction phase involved creating video presentations that detailed key comprehension strategies, such as monitoring understanding, making connections, and questioning during reading. Each video was accompanied by slide decks, which were designed to ensure consistency in instructional delivery across both courses. Slide deck/video 1 focused on monitoring and summarizing, introducing the idea of interactive reading to produce comprehension. Slide deck/video 2 focused on connections and inferencing while slide deck/video 3 focused on criticality and questioning. The modeling phase included think-alouds where instructors demonstrated the application of metacognitive strategies while engaging with academic texts (McKeown & Beck, 2009). In the guided practice phase, students applied these strategies to a text within Perusall, allowing for interaction and feedback. The guided phase also included collaboration as students were working together within Perusall. Independent use allowed students to continue using these strategies on their own, while the reflection stage provided opportunities for students to evaluate their learning and refine their metacognitive skills (Pearson et al., 2019).

Figure 1

Asynchronous Gradual Release of Responsibility Model

An Asynchronous Approach to Gradual Release of Responsibility



This iterative design ensured that the intervention was grounded in theory while being responsive to the unique needs of the students and the online learning environment. The inclusion of explicit metacognitive instruction in asynchronous courses aimed to provide a structured yet flexible approach to developing the metacognitive moves necessary for engaging with complex academic texts.

Data Collection and Participants

Data collected included student annotations made in Perusall. All graduate students ($n=32$) in both settings, representing multiple years (first year and second year graduate students) in their trajectories, were invited and agreed to participate; leaving a total of over 5,000 data points to be analyzed. A data point was a single comment on a single reading during the semester. The two settings were located in teacher education colleges in the suburban northeast, though all the students were online students they were located throughout the northeast. To manage the volume of data, analysis was limited to three participants per course ($n = 6$ total) and three texts per course, following methods from previous iterations (Adams & Wilson, 2022). Stake (2006) posits that a strategic and focused approach to data selection is crucial for uncovering meaningful insights and maintaining clarity. All participants had earned an A in the course, which is the most common grade for students in these courses, less than 5% of the

students earned a grade less than an A. The decision of choosing students who achieved an A is related to the idea that those students were more likely to attend carefully to the GRR videos and instruction to guide their reading. The three participants were based on specific criteria to serve as cases. Since about $\frac{1}{2}$ of all participants were part-time students, at least one part-time student (taking fewer than six credits) was included through random assignment. To represent the remaining half of the students, one full-time student (taking six or more credits) was included. The third participant was randomly selected to ensure a comprehensive perspective (Stake, 2006).

Participant demographics and selection reflected the populations served by the colleges; that is, while the class makeup varied minimally in terms of race/ethnicity, those selected for study were white females. No students registered for the two foci classes did not identify as white females, which matches the gender/racial make-up of the teaching force (National Center for Education Science, 2023).

This approach was designed to provide insights into the readers' metacognitive comprehension strategies during reading of high-performing students, in line with previous research on comprehension and metacognition (Mulcahy-Ernt & Caverly, 2018). Although demographic data were not collected, participant selection considered professional obligations by including both full- and part-time students, all of whom were certified teachers pursuing a master's degree in literacy education. Demographic data was not collected because the study took place during the normal process of asynchronous classes and collection of this data would have been inappropriate for an instructor to ask their students. The IRB did not approve the collection of this type of information.

Participants were assigned readings in Perusall, with one week given to complete each task. The readings differed by course: in Wilson's class, the focus was on digital literacies, while in Stevens' class, the readings centered on assessing and remediating foundational reading skills. Each author's class was a distinct data set. Both instructors/authors used the same slide decks for each instructional video, but adapted examples based on their course content. No specific number of annotations was required per reading.

For the instructional videos, a total of 96 minutes were analyzed for their efficacy to the gradual release of responsibility model (Stevens et. al., 2025) prior to analyzing the student annotations. Using the purposeful selection of readings, one from the beginning of the semester, one from the middle of the semester, and one from the end of the semester, we were left with a total of 382 student annotations across six readings down from the original 5,000. This was done because using all data points for a case study is often impractical, inefficient, and can undermine the research's focus and rigor (Stake, 2006).

Data Analysis

Annotations were coded ten months after the semester concluded, using a pre-established codebook developed in earlier iterations of the project (Adams et. al., 2023; Table 5). The coding scheme (White & March, 2006) was developed based on reading behaviors, transactions that occur during reading called comprehension strategies. The six reading comprehension strategies were identified based on a review of the literature (e.g., Gersten et al., 2001; Kamil, 2003; Snow,

2002), and operationalized as inferencing, summarizing, questions, connecting, monitoring, and synthesizing (e.g., Tompkins, 2017). Prior to this iteration, the codebook was shared multiple times with external researchers to establish reliability (Adams & Wilson, 2022). The research team ensured inter-rater reliability through practice coding and multiple rounds of review, achieving a reliability rate of over 95% (Creswell & Poth, 2016). The reliability came from first coding as a group 25% (96) of the responses, then coding with research partners the remaining 75% (286) of the responses. The full research team then came together to check the reliability of the coding, noting each time codes did not match, only $n=19$ times. These codes were discussed and then recoded through a final agreement with the full research team. Coding focused on identifying key metacognitive and comprehension strategies (metacognitive moves), such as questioning, summarizing, and making connections (Mulcahy-Ernt & Caverly, 2018; Soto et al., 2023). The primary goal was to evaluate whether the instructional videos effectively supported students' metacognitive moves during reading, which refer to a student's conscious decision to show their thinking. The strategy we identify is what we infer that the reader did when they chose to annotate at that point. The annotation is purposeful and thus a metacognitive move.

Findings

This section examines the impact of explicit metacognitive instruction using the GRR framework by comparing findings across different iterations and analyzing differences between the two courses under investigation. In all iterations the same two courses were foci of the research. Though both courses are part of literacy graduate programs that prepare literacy specialists, they differ significantly in content focus. Wilson's course on digital literacies explores the evolution of print versus online reading, media literacy, and critical comprehension in digital contexts, while Stevens' course on foundational reading skills addresses phonics, phonemic awareness, and the instruction of basic reading components. Both programs teach the same content, examining two different courses in the programs allows for the examination of the gradual release model. Prior research does not address content differences in this framework. The data for 2021 was coded and published prior to this work (Adams et. al., 2023). The data for 2023 was coded using the pre-existing codebook thus allowing for some comparison. Given the differing demands of these courses, they provide an opportunity to examine how instructional design, text complexity, and domain knowledge shape graduate students' use of metacognitive reading strategies.

The first part of this section compares findings from the 2023 iteration to previous versions of the study to assess whether explicit GRR instruction influenced students' metacognitive engagement. The second part examines how metacognitive strategy use differed between the two courses, highlighting how content and pedagogical context affected the application of specific reading strategies.

Comparing 2023 Findings to Previous Iterations

Prior research on graduate students' metacognitive reading behaviors (Adams & Wilson, 2022) found that students primarily engaged in text-to-self connections when annotating academic texts. While making connections is a valuable reading comprehension strategy, these earlier findings suggested that students were not engaging in higher-order metacognitive moves such as questioning, synthesizing, or monitoring. In the current iteration, we wanted to see if

explicit strategy instruction using the GRR framework would expand students' use of questioning and monitoring strategies compared to previous studies (Adams et al, 2023).

To further understand this, both the 2021 and 2023 datasets were analyzed using a consistent coding framework, with percentages adjusted to account for differences in the number of readings per iteration. It is appropriate to use percentages because these are observations that exist for data points. Since the number of participants is small, we used percentages to see if there is any relationship between the types of strategies exhibited with no explicit instruction in GRR, and then with explicit instruction in GRR. Since the purpose of this research is formative, the percentages are appropriate for gathering a snapshot of the strategies used. The goal here was to uncover a quintain (Stake, 2006). Because the 2021 study examined only two readings, we excluded Reading 3 from the 2023 dataset to ensure comparability. The analysis revealed several key differences. First, whereas the 2021 dataset showed an over-reliance on making connections, the 2023 data reflected a broader distribution of metacognitive strategies, including a noticeable increase in questioning and monitoring (See Table 3). This shift suggests that students exposed to explicit metacognitive instruction diversified their reading strategies beyond surface-level connections. Second, the nature of connections changed: While text-to-self connections dominated in 2021, students in 2023 engaged in more text-to-text connections, indicating that they were synthesizing ideas across multiple sources rather than merely relating content to personal experiences.

Table 3

Total Strategy Usage Comparison from 2021 to 2023

	Wilson, 2021	Wilson, 2023	Stevens, 2021	Stevens, 2023
Connecting	45.90%	42.19%	67.65%	36.73%
Inferring	3.28%	5.47%	2.94%	0.68%
Questioning	4.92%	17.19%	5.88%	7.48%
Monitoring	34.43%	27.34%	23.53%	53.06%
Summarizing	6.56%	2.34%	0.00%	1.36%
Synthesizing	4.92%	5.47%	0.00%	0.68%

Taken together, these findings support the initial conclusion that explicit instruction in metacognitive reading behaviors encouraged a wider repertoire of strategies, enabling students to engage more critically and reflectively with academic texts. However, while questioning and monitoring increased, the frequency of synthesis remained lower than anticipated, suggesting that additional scaffolding may be needed to help students integrate and apply information across texts.

Explicit Instruction and Metacognitive Development

In this iteration, the GRR framework (Pearson & Gallagher, 1983; Pearson et al., 2019)—incorporating explicit description, modeling, collaborative use, guided practice, independent use, and reflection—was adopted to enhance students’ metacognitive moves beyond the connections observed in earlier iterations. Explicit strategy instruction provided through the recorded videos increased the likelihood that student annotations would reflect those modeled strategies, as evidenced by their more varied use of metacognitive moves. These findings suggest that explicit instruction in metacognitive reading behaviors did support students’ engagement with strategies such as questioning and monitoring. However, the extent of this impact varied depending on both course content and instructional approach, with some students demonstrating greater flexibility in strategy use than others (Stevens et al., 2025). The unique nature of each course could have impacted the strategy use by students, thus comparing the courses using inferential statistics would not be appropriate.

Findings Related to Instructional Intervention

After coding all data using the pre-existing codebook (see Appendix), we analyzed the 2023 dataset to identify patterns and trends in strategy usage aligned with the GRR video instruction in these cases. The GRR framework incrementally introduced different metacognitive strategies: The first video focused on introducing metacognition and monitoring; the second emphasized making connections, especially text-to-text; and the third focused on questioning and criticality.

The findings indicate that students responded to explicit instruction by increasing their use of modeled strategies. Table 3 presents the percentage of overall annotations for each metacognitive move, across the two courses taught by Wilson and Stevens. The data seems to reveal patterns that align closely with the instructional focus of each video. For example, monitoring was prominent in the codes for Reading 1, making up 39% (numbers have been rounded for clarity) of annotations in Wilson’s course and 63% in Stevens’ course, consistent with the first video’s emphasis on monitoring. Similarly, connections dominated Reading 2 for both courses, reflecting the second video’s focus on making explicit connections.

Table 4

Strategies from Readings 2023

Strategy	Wilson, Reading 1	Stevens, Reading 1	Wilson, Reading 2	Stevens, Reading 2	Wilson, Reading 3	Stevens, Reading 3
Connecting	39.29%	28.97%	54.48%	60.53%	50.00%	49.02%
Inferring	7.14%	0.93%	4.83%	0.00%	3.49%	0.00%
Questioning	7.14%	4.67%	10.34%	15.79%	17.44%	13.73%
Monitoring	39.29%	63.55%	26.21%	21.05%	22.09%	37.25%
Summarizing	5.36%	0.93%	0.69%	2.63%	1.16%	0.00%
Synthesizing	1.79%	0.93%	3.45%	0.00%	5.81%	0.00%

In Reading 3, questioning increased noticeably in Wilson’s course, rising from 10% in Reading 2 to 17% in Reading 3, aligning with the instructional video’s focus on questioning. However, connecting remained a substantial strategy, holding at 50% of codes in Reading 3. In

Stevens' course, monitoring remained a dominant strategy across readings, particularly in Reading 3, where it made up 37% of the codes.

Interpretation of the Findings

The alignment between the explicit instruction provided in the videos and the strategies used in the annotations suggests that the GRR framework had a meaningful impact on students' metacognitive reading behaviors. The focus on monitoring in the first video resulted in a high percentage of monitoring annotations in the corresponding reading, while connections and questioning increased when they were emphasized in subsequent videos. However, the persistence of monitoring as the dominant strategy in Stevens' course suggests that some students may require additional instruction and opportunities for practice before they can transition to more flexible metacognitive strategy use.

The difference in strategy use between the two courses points to a key consideration: while explicit instruction is an effective intervention, it may not be sufficient as a standalone approach, particularly for students engaging with content-heavy, technical readings. The students in Stevens' course, despite exposure to the same metacognitive framework, continued to rely on monitoring, which suggests that they may not yet feel confident in applying strategies such as questioning and synthesis. Rather than reflecting a failure of explicit instruction, this finding indicates that sustained and reinforced instruction may be necessary to help students move beyond comprehension monitoring and toward higher-order engagement with texts.

Wilson: Digital Literacies

The content of Wilson's course, focusing on digital literacy, required students to question and engage critically with the text. Wilson's instructional videos stressed the importance of critical reading and responding to texts to become better readers and teachers. A key instructional move was the deliberate pausing in the videos to allow students to reflect and process information, alongside quizzes that reviewed key terms discussed in the videos.

The impact of these instructional strategies is clear in the students' annotations. In the first recorded video, which focused on monitoring, student annotations showed a balance between monitoring and connecting strategies. Previously, connecting had been the most common strategy (Adams & Wilson, 2022). However, after explicit instruction on monitoring, the percentage of annotations coded for monitoring was equal to those for connecting. This shift highlights the role of targeted instruction in encouraging a wider use of metacognitive strategies.

In the second recorded video, Wilson focused on making connections and inferences, encouraging students to go beyond simple text-to-self connections. For example, one student wrote, "This parallels Leu's comments about how we critique media evolving as rapidly as digital spaces are," demonstrating a deeper text-to-text connection. This level of engagement contrasts with prior iterations, where text-to-self connections were far more common, such as, "I think my life would be different if I had grown up with social media." By promoting text-to-text connections, Wilson encouraged richer, more analytical thinking in the annotations.

In addition to connecting, questioning also increased in Reading 2, likely due to Wilson's focus on using questioning to guide connections. One notable student annotation asked, "I want

to think about this in terms of teaching. How can we leverage all our students' knowledge and have them share what they know? We should position them as capable and collaborative as described in Johnston (2023).” This kind of questioning demonstrates a deeper engagement with the material and a move toward more critical reflection, which was encouraged through explicit instruction in the videos.

Stevens: Phonological Awareness and Assessment

Stevens' course focused on assessment-driven instruction of reading foundational skills, with the students using the same text (Kilpatrick, 2016) throughout the course. Despite having prior knowledge of the content from a previous foundational course, many students expressed uncertainty and anxiety about their understanding of the vocabulary and concepts. For example, one student noted, “I have read this about 5 times, and I’m still trying to make sense of it.” Another student similarly reflected, “I always had a hard time differentiating between phonological awareness and everything else under its umbrella.” This is of particular importance regarding understanding the candidates' metacognitive moves because,

Ultimately, the construction–integration model provided a more complete description for how readers use textual information and their background knowledge to construct several increasingly refined mental models of the text, including a text base that was literal and fleeting and a situation model that was interpretative and stable (Dewitz & Graves, 2021, p. S133).

The students' lack of confidence and confusion around the concepts in the class demonstrate a lack of background knowledge regarding the specifics of the course content.

These insecurities were observed within the students' annotations, with much of their focus on monitoring their own understanding. While Stevens' instructional videos included enactments and modeling of strategy application, opportunities for student practice were less frequent than in Wilson's course. In the first recorded video, which focused on summarizing and monitoring, students were explicitly encouraged to avoid simple text-to-self connections. Stevens told students, “I am trying to release responsibility to you now that I have modeled,” clearly demarcating the shift toward independent use.

However, many students had difficulty moving beyond monitoring their basic understanding of the course concepts. One student commented, “I think I now understand the difference between phonological awareness and phonemic awareness,” (Reading 2) reflecting the cognitive effort required to grasp the foundational knowledge. As a result, monitoring remained the dominant strategy throughout the readings, indicating that the students were still working through essential content comprehension rather than engaging in deeper questioning or connections.

Discussion

This iteration of the study, which incorporated explicit instruction within the GRR framework, produced more varied metacognitive comprehension strategic reading compared to

previous iterations. However, differences emerged between the two courses, likely influenced by the nature of the texts assigned and the instructional moves made by each author.

Wilson's focus on digital literacy introduced texts that encouraged critical engagement and questioning. Research shows that the complexity and genre of texts can affect students' metacognitive engagement, with expository texts often demanding more monitoring and inferential strategies, while narrative or more open-ended texts may encourage greater connections and critical reflection (Kintsch, 1998; McNamara, 2004). The explicit emphasis on questioning as a strategy, coupled with opportunities for students to practice, likely contributed to the increase in questioning annotations and the deeper, more varied connections observed in the 2023 data. By contrast, Stevens' course on reading foundational skills relied on a text that was more content-heavy and less conducive to critical questioning. Consequently, the students' annotations reflected a focus on monitoring their comprehension, which is consistent with findings that content-heavy texts require greater monitoring to manage comprehension (McNamara, 2004).

While both courses used the same GRR-based slide decks, the primary difference lay in how the content was modeled. The GRR framework has been shown to effectively scaffold student learning by gradually shifting responsibility for strategy use from the teacher to the student (Pearson & Gallagher, 1983; Fisher & Frey, 2014). Wilson provided more opportunities for practice and reflection, with quizzes used to assess understanding at the end of each video. In contrast, Stevens' videos featured more teacher modeling with fewer explicit prompts for student engagement during the lesson (Stevens et al., 2025). As a result, the students in Wilson's course demonstrated greater variety in their use of metacognitive strategies, while students in Stevens' course remained more focused on literal comprehension and monitoring.

These findings align with research that suggests explicit instruction within the GRR framework can support metacognitive development, but that the students' background knowledge, type of text, and small differences with instructional approach (Stevens et al. 2025) could influence the depth and variety of strategy use (Pearson & Gallagher, 1983). Further iterations should explore how to better scaffold students who are working with content-heavy texts, with which they have little background knowledge, and how to encourage the use of more varied strategies beyond monitoring.

Limitations

While this study provides valuable insights into the impact of explicit metacognitive instruction using the GRR framework, several limitations should be considered when interpreting the findings. These limitations primarily relate to instructional variability between the two courses, sample size constraints, and data collection methods. The use of percentages to compare the data is appropriate for this initial case study, however a larger study using inferential statistics should be considered for making definitive conclusions.

Although both courses followed the GRR framework and provided explicit metacognitive instruction, the way each instructor implemented the model varied. The digital literacies course incorporated structured self-assessment activities, such as quizzes and guided reflection prompts, while the foundational reading skills course relied more heavily on teacher modeling with fewer

explicit opportunities for structured independent reflection. These differences may have contributed to the observed disparities in metacognitive engagement across the two courses. While the study identifies instructional design as a key factor influencing metacognitive strategy use, it is difficult to isolate the effects of explicit instruction from the differences in presentation style between the two instructors. Future research should explore whether a standardized implementation of GRR, with consistent scaffolding across courses, yields different results.

Another limitation of this study is the small number of participants, which limits the generalizability of the findings. Because the study was conducted within two graduate courses, the sample size was constrained by course enrollment numbers. As a result, it is unclear whether these findings would hold across a larger, more diverse population of students. Future studies should examine larger sample sizes across multiple institutions to determine whether similar patterns of metacognitive engagement emerge in different educational settings. Additionally, examining student demographics, prior coursework, and reading backgrounds could provide further insight into how different factors influence metacognitive development.

This study relied on students' Perusall annotations as the primary measure of metacognitive strategy use. While this method provides a valuable window into students' reading engagement, it does not capture other forms of metacognitive processing, such as silent reflection, unrecorded thoughts, or strategy use that occurs outside the annotation platform. Some students may have engaged in questioning or synthesis while reading but did not record these moves in their annotations, potentially underestimating their true metacognitive engagement. Future research should incorporate think-aloud protocols, interviews, or reflective journals to gain a more comprehensive understanding of how students engage with metacognitive strategies beyond what is visible in their annotations.

Finally, it is possible that students' annotation behaviors were influenced by their understanding of instructor expectations. Students in the digital literacies course, for example, may have engaged in more questioning and synthesis because they recognized that these strategies were emphasized in instructional videos and quizzes. Similarly, students in the foundational reading skills course may have focused more on monitoring because they perceived comprehension checking as the most relevant strategy for engaging with technical material. Future research could explore whether explicit grading criteria or instructor expectations shape students' metacognitive engagement and how instructional framing influences students' selection of reading strategies.

Implications

The findings from this iteration highlight the importance of explicit metacognitive instruction in supporting students' use of reading strategies. While the GRR framework had a positive impact, data across all iterations of this research reveal areas for further attention. Two key concepts emerged that merit ongoing consideration for teacher educators: (1) graduate students' metacognitive skills and (2) the need for sustained instruction across courses.

Graduate Students' Metacognitive Skills

Across iterations, a consistent finding is that graduate students, even in literacy programs, are not necessarily metacognitive readers. Prior research shows that metacognitive skills do not

always develop alongside academic advancement, and even experienced educators may have difficulty engaging reflectively with texts (Pressley & Afflerbach, 1995; Schraw & Moshman, 1995). This challenges the assumption that graduate students arrive with well-developed metacognitive skills.

This finding is particularly important given the role of graduate students as future literacy specialists. If they do not consistently model strategic reading themselves, they may lack the confidence to teach it. Research suggest that K–12 comprehension instruction often falls short of evidence-based practice (Dewitz & Graves, 2021), which may contribute to gaps in educators' own metacognitive development. These findings suggest that teacher preparation programs should not only teach about comprehension instruction but also embed metacognitive strategy instruction as part of graduate coursework.

The Need for Sustained Instruction Across Courses

A second key implication is that one-time instruction is insufficient to support lasting metacognitive growth. Strategy development is gradual and requires repeated, scaffolded practice across different courses and contexts (Palincsar & Brown, 1984; Paris & Winograd, 1990). While explicit instruction improved students' use of questioning and monitoring, our findings suggest that these gains may not endure without reinforcement.

The contrast between the two courses reinforces this need. Students in the digital literacies course, who engaged in structured reflection, showed greater flexibility in applying strategies. Meanwhile, those in the foundational reading skills course, who did not receive consistent reflection prompts, primarily relied more on monitoring. This suggests that even with the same instructional framework, metacognitive development depends on consistent opportunities to apply and reflect on strategies across contexts. To support transfer and long-term growth, teacher educators should embed metacognitive strategy instruction across multiple courses, not as an isolated intervention but as an integral part of curriculum design. Doing so can help future teachers develop adaptable reading skills that extend beyond specific assignments or content areas and prepare them to teach these strategies with confidence in diverse classroom contexts.

Future Research

These findings suggest several key directions for future research. First, further study is needed to better understand why graduate students may have difficulty with metacognitive reading and how teacher education programs can better support their development in this area. Research on K–12 literacy instruction suggests that comprehension instruction has not always followed evidence-based practices (Dewitz & Graves, 2021), raising important questions about how educators' prior experiences with reading instruction shape their metacognitive skills in adulthood. Second, research should explore the long-term impacts of sustained, cross-curricular metacognitive instruction. Future studies should examine how embedding metacognitive strategy instruction across multiple courses affects students' ability to transfer and apply strategies in different academic contexts. Finally, future research should investigate the role of student agency in metacognitive engagement. Understanding how students choose and regulate their metacognitive strategies could inform instructional approaches that better support self-regulated learning and critical engagement with texts (Flavell, 1979; Schraw & Dennison, 1994).

Conclusion

This study offers important insights into how explicit metacognitive instruction, delivered through the GRR framework, can support graduate students' development as strategic readers. While instruction led to a broader range of strategy use, especially questioning and monitoring, the effectiveness varied depending on course content, student backgrounds, text complexity, and instructional approach (see Stevens et al., 2025). Findings across all four iterations of this research consistently point to three key challenges. First, graduate students, even those in literacy-focused programs, may not enter with strong metacognitive reading habits, challenging assumptions in teacher education (Pressley & Afflerbach, 1995; Schraw & Moshman, 1995). Second, metacognitive development requires more than a one-time intervention. It benefits from sustained, embedded instruction across multiple courses to support transfer and long-term use (Palincsar & Brown, 1984). Third, students exercise agency in how they engage with texts, suggesting that instruction must go beyond teaching strategies to support reflective decision-making about strategy use.

These insights carry implications for program design and the preparation of literacy educators. To foster truly strategic readers, teacher education programs must build metacognitive instruction into the curriculum in recursive, contextualized ways. In so doing, future educators will be better equipped to model and teach comprehension strategies in K–12 classrooms, supporting a more reflective and responsive literacy pedagogy.

Declarations

The authors have no competing interests to declare.

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Appendix

Codebook

		Level 1	Level 2	Level 3
Strategy	Definition/Examples	Lip Service	Surface	Strategy for Understanding
Inferencing	• Drawing on information from the text and background knowledge to understand what the text is about • Filling in details missing from the text • Elaborating on what is discussed in the text	When students are asked to name the strategy used, they reply with X, but we don't see the strategy	We see the strategy and would code without student identification, but we cannot tell how the strategy builds understanding of the content	We see the strategy and would code without student identification, and we can tell how the strategy builds understanding of the content
Summarizing	• Restating key ideas from some unit of text (e.g., chapter, page, section) • Determining what is most important to remember in a unit of text	When students are asked to name the strategy used, they reply with X, but we don't see the strategy	We see the strategy and would code without student identification, but we cannot tell how the strategy builds understanding of the content	We see the strategy and would code without student identification, and we can tell how the strategy builds understanding of the content
Questioning	• Asking questions of the text • Asking questions that extend the text • Challenging the text/disagreeing	Student asks a question, but not to the text (not asking as a reading strategy—asking to prof or peers)	Students ask a question of the text, but the question removes them from the main idea of the text	Student asks questions of the text that builds understanding of the reading and/or course in general
Connecting	• Making connections to prior knowledge • Making connections to praxis • Making text-to-text connections (includes academic learning experiences)	Student makes connections with no explanation	Student makes connections with citation or explanation, but it is unclear how it leads to understanding of the content (connection could even take away from the content)	Student makes connections with citations and/or explanations, and it is clear how the connection builds understanding of the text or course content

	• Making text-to-self connections (personal experience) • Making text-to-world connections (generalized experience)			
Monitoring	• Confirming or clarifying understanding of what is in the text • Looking up and defining words used in the text • Restating what is in the text • Generating questions about praxis	When students are asked to name the strategy used, they reply with X, but we don't see the strategy	We see the student is looking up a word or doing something, but what they are doing is not monitoring the text as a whole	The students is monitoring and making clear developments in concept formation
Synthesizing	• Making connections between multiple sources • Connection to a point earlier in text	When students are asked to name the strategy used, they reply with X, but we don't see the strategy	We see the strategy and would code without student identification, but we cannot tell how the strategy builds understanding of the content	We see the strategy and would code without student identification, and we can tell how the strategy builds understanding of the content
Community	Definition/Examples	Lip Service	Surface	Strategy for Understanding
Questioning	• Initiating a comment thread by asking a question • Asking questions of a peer or peers within a comment thread	"I wonder" with no connection to the readings or course	Looking for understanding, i.e., "What does this word mean?" without any follow up.	Probing classmates to think more deeply or make a connection. Asking a question directly related to the reading and/or previous readings with the connection explicit.

Restating	• Restating something another peer posted • Agreeing with comments posted by another peer or peers			
Additive	• Adding to or augmenting a comment made by a peer or peers • Challenging the ideas within another peer's comment(s)	Adding without augmenting	Challenging the ideas of a peer's comment	Challenging the ideas of a peer's comment to develop course understandings or conceptual understandings of literacy teaching and learning

Instructors' Perceptions of Assessment Types and Strategies Used in Online Courses in Higher Education

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Abstract

Limited research has focused specifically on the effectiveness of assessments in online learning environments. Using the assessment dimension of the IDEAS Framework for Teaching Online, this study used a survey methodology to investigate instructors' perception of the effectiveness of assessment types and strategies used by online instructors in higher education. Instructors at two universities and one professional organization were invited to participate in the study. One hundred and four individuals completed the survey. Results showed that instructors considered design and multimedia projects as the most effective assessment types. Instructor-graded and individual student assignments were considered the most effective strategies by online instructors. Results indicated non-proctored exams and ungraded assignments were considered the least effective assessment type and strategy. Most instructors used text-based feedback and provided feedback on assignments within a week. Significant correlations were found between instructors' characteristics and preference for certain assessment types and strategies. Results are discussed in the context of the literature.

Keywords: Higher education; online assessment; assessment types; assessment strategies

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Introduction

Assessment is an important element in online teaching and learning (Kearns, 2012; Moore & Kearsley, 2012). Assessment “provides evidence of the outcome in any outcomes-based approach to education” (Conrad & Openo, 2018, p. 5). It also provides information to students regarding their learning and performance and can impact learner motivation (Rovai et al., 2008). Assessment assists the faculty and administrators to measure and monitor students’ progress and performance (Sewell et al., 2010).

Conrad and Openo (2018) pointed out that assessment in online environments “adds another level of complexity” (p. 3). Gaytan and McEwen (2007) emphasized that “using effective assessment techniques is an essential part of effective teaching and learning in the electronic environment” (p. 118). It is essential to align assessments with learning activities and learning objectives (Dabbagh & Bannan-Ritland, 2005; Ko & Rossen, 2010; McKeachie & Svinicki, 2006). Feedback, a part of the assessment cycle, is essential and critical to student learning. Good feedback identifies achievement gaps, and learners may use feedback to improve their performance (Henderson et al., 2021; Hooda et al., 2022).

Robles and Braathen (2002) raised interesting questions regarding online assessments. How do we measure learning outcomes, and which assessments are necessary? According to Conrad and Openo (2018), conducting assessments in online environments makes the process more complex. There is limited research on the effectiveness of assessments in online learning environments, particularly research that focuses on online instructors’ perceptions of the effectiveness of assessment activities and strategies, and feedback in online learning environments. The purpose of the study was to investigate perceptions of online instructors in higher education pertaining to the effectiveness of different online assessment types and strategies.

Literature Review

There are a variety of learner assessments that can be integrated in online courses and or programs. Reeves (2000) pointed out that instructors who teach online courses focused too much on the assessment of learners’ retention of knowledge in the past instead of the application of newly acquired knowledge. The focus, he suggested, should not be on retention but on higher-order educational objectives in the cognitive domain identified by Bloom (1956), like application, analysis, synthesis, and evaluation.

Instead of using more traditional assessments to test learners’ retention and understanding of knowledge, alternative assessments can be used to evaluate high-order skills. The use of alternative assessment has the potential to improve student learning in online environments in higher education. Reeves (2000) mentioned three approaches for integrating alternative assessment: cognitive, performance, and portfolio assessment. Cognitive assessment refers to the assessment of higher-order thinking and communication skills and attitudes. The learner’s demonstration of applying knowledge through participating in activities or creating products refers to performance assessment. Portfolio assessment allows learners to archive products they created over time to provide evidence of learning and their process of knowledge and skills

acquisition. These products can also be used for reflection pertaining to the learner's engagement, experience, and progress (Conrad & Openo, 2018).

Important characteristics of assessments include criteria and standards that communicate expectations to learners (Conrad & Openo, 2018). Melo et al. (2022) studied learners' preferences for assessment formats or types. Additionally, they classified several assessment attributes. Results showed that the three preferred assessment attributes by learners were driving, realistic, and pertinent, whereas the least important attributes were fast, strategic, and safe.

Conceptual Framework

The IDEAS Framework for Teaching Online includes assessment as one of the dimensions (Martin & Ritzhaupt, 2023). Other dimensions in this framework are Design, Engagement, Evaluation, Support, and Inclusion. Figure 1 includes the various aspects to consider when designing and implementing assessments in online courses. This framework along with the review of literature was used to guide us in the design of the survey on assessment types, strategies, and feedback.

Figure 1

Assessment in Online Courses

IDEAS Framework for Teaching Online—Assessment Dimension	
● Gauging Prior Knowledge, Skills, and Attitudes ● Formative and Summative Assessments ● Participation Credit for On-Task Behaviors ● Traditional and Authentic Assessments ● Provide Tailored Feedback ● Automated Assessments	

Assessment Types

Rovai et al. (2008) points out that many assessments that can be integrated in campus-based courses can also be used in online courses. "Assessment type refers to the implemented task of the assessment" (Heil & Ifenthaler, 2023, p. 190), such as quizzes and essays. Gaytan and McEwen (2007) stressed that a variety of well-explained assessments should be used regularly in online courses because it provides instructors with an opportunity to become familiar with students' work, increases levels of interactions, and provides learners with frequent feedback. Morgan and O'Reilly (1999) suggested a variety of online assessment methods based on eight different learning activities: critical thinking, problem solving, demonstrating procedures, managing oneself, accessing and managing information, demonstrating understanding, designing or creating a product, and communicating.

One of the most common assessments in online higher education are written assignments (Sewell et al., 2010; Swan, 2001). These types can test learners' higher-order thinking skills such as analysis and synthesis and may include essays, reports of fieldwork or statistical analysis,

statistical write ups, plans (lesson plans, business plans), summaries, and literature reviews or annotated bibliographies (Kearns, 2012; Heil & Ifenthaler, 2023; McVey, 2016). Another assessment that allows learners to demonstrate skills in these cognitive domains is a case study analysis, where learners break a case into parts and provide solutions and recommendations (Kearns, 2012; Melo et al., 2022; Sewell et al., 2010).

Swan (2001) found that the most common assessments in online courses were tests, quizzes or examinations and other experts mention them in the literature (Gaytan & McEwen, 2007; Kearns, 2012; Melo et al., 2022; Robles & Braathen, 2002; Sewell et al., 2010; Xiong & Suen, 2018). Questions on quizzes and examinations solicit either a select- or construct-response from a learner. A select-response question requires learners to choose a response such as multiple-choice, true/false, match items, whereas a constructed-response question asks learners to create their own answers to open-ended-questions, scenarios, essays, etc., in order to assess a learner's ability to think critically (McVey, 2016; Rovai et al., 2008; Sewell et al., 2010; Xiong & Suen, 2018). These assessments may be timed or monitored (Gaytan & McEwen, 2007). Some exams that are part of a professional certification may be remotely proctored or monitored on an on-site testing center for security purposes (Melo et al., 2022; Sewell et al., 2010; Xiong & Suen, 2018).

There are several types of deliverables associated with assessment (Rovai, 2008), and Melo et al. (2022) make the distinction between product versus non-product producing assessments. Some of the types included in a variety of assessments are project-based assignments (Gaytan & McEwen, 2007; Marquis, 2021; Melo et al., 2022; Sewell et al., 2010). These can be authentic assessments that apply to real-world situations or scenarios where learners apply newly acquired skills to work with clients, either individually or in teams, in order to create a product. Examples are multimedia projects where learners produce digital files such as audio or video or design projects where learners engage in the instructional design process to produce instructional units, learning content, or digital artwork (Heil & Ifenthaler, 2023). Learners may be tasked to deliver write-ups of statistical analyses for research projects or collect artifacts they created over time to develop portfolios.

One assessment type that has become popular over the years are electronic portfolios or ePortfolios. Individual learners create assignments or artifacts over time, collect them, and store them electronically for review by other learners and instructors to demonstrate knowledge, skills, and abilities. They may also be used by learners as self-reflection tools pertaining to how learning occurred and the amount of knowledge or number of skills acquired over time (Gaytan & McEwen, 2007; Heil & Ifenthaler, 2023; Marquis, 2021; Melo et al., 2022). Bolliger and Shepherd (2010) found the majority (67.5%) of students valued the integration of ePortfolios in an online graduate program.

Reflections lend themselves well to online learning because most of the course content is text-based and learners can think more deeply due to the time factor involved. Educators may use written assignments (e.g., journals, papers) for critical reflections pertaining to processes such as knowledge building, personal growth, group work, and so forth. These assignments may be shared with the instructor and with peers (Conrad & Openo, 2018; Sewell et al., 2010).

Simulations and virtual laboratories are instructional tools for learners to engage with learning content actively, and Gaytan and McEwen (2007) found they were considered effective assessment techniques by instructors and students. Assignments may be completed individually or in groups. These environments may be a good choice for learners to acquire technical skills visually and test their comprehension and application of subject matter; however, the design of these environments is sophisticated and requires learners to have adequate computer systems and good infrastructures (Melo et al., 2022; Rovai et al., 2018; Sewell et al., 2010).

In order to facilitate discourse, engage learners, and build community in online courses, many instructors implement participation activities in the form of online discussions (Chen et al., 2021; Gaytan & McEwen, 2007; Kearns, 2012; McVey, 2016; Melo et al., 2022; Robles & Braathen, 2002; Sewell et al., 2010; Xiong & Suen, 2018). Discussions may be structured or unstructured, and instructors may choose to use small group or whole class discussions, or a combination of both (Fehrman & Watson, 2021; Kearns, 2012).

Self-assessment exercises are typically not graded such as self quizzes or practice tests (Bolliger & Martin, 2021; Chen et al., 2021; Gaytan & McEwen, 2007; Robles & Braathen, 2002; Sewell et al., 2010). These assessments can include (Whitworth & Wright, 2015) drill and practice or real-time quizzes (Chen et al., 2021), and question and answer sessions (Xiong & Suen, 2018).

Assessment Strategies

Rovai (2008) categorized two categories of assignments: independent work where learners are responsible for completing assignments by themselves (Melo et al., 2022), and collaborative assignments where teams or groups of students are contributing to the assignment (Altinay, 2017; Bolliger & Martin, 2021; Marquis, 2021; Melo et al., 2022). Assessments can be formative or summative. Formative feedback provides instructors with the ability to have more frequent interaction with learners and more opportunities to widely disseminate feedback to students. It allows learners to improve their performance over time (Bolliger & Martin, 2021; Chen et al., 2021; Halupa & Bolliger, 2013; Heil & Ifenthaler, 2023; McVey, 2016; Melo et al., 2022; Rovai et al., 2008; Sewell et al., 2010). In contrast, summative assessments are administered at the end of an instructional period. Summative assessments are considered high stakes testing because they are associated with the assignment of grades (Bolliger & Martin, 2021; McVey, 2016; Melo et al., 2022; Rovai et al., 2008; Sewell et al., 2010). Additionally, assessments may be either formal (or graded) or informal (not graded). Like with formative assessments, instructors who integrate informal assessments can identify learners' weaknesses and allow them to improve their performance (Rovai et al., 2008).

Differentiated assessments in online courses involve tailoring or personalizing them to meet the needs and preferences of diverse students. This assists students who take online courses with varying prior knowledge, goals, and learning pathways. Differentiation could be varied such as choice in assessments and assessment topics (Martin & Bolliger, 2018; Pinchot & Poullet, 2021), adaptive learning paths (Cai, 2018; Cordova, 2023), and flexible assignments (Rideout, 2017).

Instructors may also use open-book exams to evaluate learners' application of newly acquired knowledge (Melo et al., 2022) or may allow multiple attempts. Lee et al. (2021) who focused on self-directed learning in their research found the majority of students who were able to take online tests with multiple-choice questions multiple times did not guess answers to the questions; instead, they showed interest in learning. Brazhkin and Strakos (2023) found that students in management courses who had to enter quantitative answers preferred three attempts.

Another online assessment strategy is the use of peer review (Marquis, 2021; McVey, 2016). This strategy allows learners to provide and receive feedback and get exposed to other learners' ideas and writing styles. Peer assessments allow learners to learn about criteria for assignments, observe their peers' performance, and improve their own work (Van Popta et al., 2017; Van der Pol et al., 2008). However, learners should be provided with structure and information on how to provide effective feedback to other students. Kearns (2012) suggested providing learners with a grading rubric to provide their peers with clear and consistent feedback. Marquis (2021) pointed out that online annotation tools such as Google Docs can be used to provide learners with a more dynamic exchange of feedback by all course participants. When collaborative assessments are used in online courses, peer evaluations may be useful to determine individual efforts of team members (Gaytan & McEwen, 2007; Melo et al., 2022; Rovai et al., 2008).

Another commonly used strategy is the use of grading rubrics (Bolliger & Martin, 2021; Conrad & Obeno, 2018; Gaytan & McEwen, 2007). Instructors may use grading rubrics that include the purpose of the assessment, learning objectives, and criteria/standards (Conrad & Obeno, 2018) as an internal tool for grading student work consistently. Instructors may also post them to communicate expectations to learners. Often, this strategy results in fewer questions from learners pertaining to course assignments, therefore reducing the instructor's workload (Ko & Rossen, 2010).

Feedback

Feedback plays a vital role in the student learning process in online courses, and promotes learners' engagement, reflection, and growth. It may be corrective or elaborative (Heil & Ifenthaler, 2023). Feedback on assignments can be provided through different mechanisms. Different modes can include computer -assisted or automated, and instructor or peer feedback; self-assessments; and feedback generated by artificial intelligence (Heil & Ifenthaler, 2023; Hooda et al., 2022; Ogange et al., 2018; Rovai et al., 2008). Some instructors have also used peer assessment that can be formative or summative (Altinay, 2017; Kearns, 2012; Xiong & Suen, 2018). Rovai et al. (2008) pointed out that peer feedback may either be blinded or unblinded.

As previously mentioned, feedback is an important consideration in effective teaching and learning. Gaytan and McEwen (2007) point out that feedback should be timely and meaningful. Weekly assignments such as quizzes are a good type of assessment to provide immediate feedback to learners. The majority of instructors and students who participated in a study conducted by Gaytan and McEwen (2007) thought that continuous, immediate, and detailed feedback was an important consideration in quality online teaching. There are also different kinds of feedback modalities. Feedback may be given via video (Ketchum et al., 2022), audio or text (Hooda et al., 2022).

Instructor Characteristics and Context

Gaytan and McEwen's (2007) who conducted a study pertaining to online instructors' perception of effective assessment strategies found that most participants were female, regular faculty members, and many were at least 50 years of age. Additionally, instructors were well-experienced teachers in both the higher education setting and the online teaching environment. In a study conducted by Inan and Bolliger (2024), results showed that instructors with constructivist pedagogical beliefs chose to use more student-centered learning activities than instructors with more traditional beliefs. However, there is limited information on how instructor characteristics may influence assessment practices.

Other experts (Ko & Rossen, 2010; McKeachie & Svinicki, 2006) provided guidance on how to facilitate and assess student learning in classes of different sizes. In large classes, for example, instructors may use automated grading, student presentations, small group projects, peer evaluations, and so forth. Additionally, instructors may use different assessment types and strategies based on course level (undergraduate vs. graduate). According to Enright and Gitomer (1989), "goals of graduate education include training of researchers, teachers, and practitioners" (p. 4). Graduate programs prepare learners for professions and should train learners to identify problems; write proposals, papers, and reports; and provide constructive feedback to peers. These tasks are aligned with higher-order thinking skills that may require the development of learning objectives different from undergraduate-level courses.

Purpose of the Study and Research Questions

This study investigates online instructors' perspectives on the effectiveness of different assessment types and strategies. While assessments have long been part of teaching and learning, limited research has focused specifically on the effectiveness of assessments in online learning environments. By considering varied assessment types, strategies for implementation, and contextual factors such as course level (undergraduate vs. graduate) and class size (small vs. large), this study contributes new insights to the field. It also examines the role of feedback—both in terms of modality and frequency—as a key element of successful online courses.

This study answers the following research questions:

1. What are effective assessment types and strategies used by instructors in online courses in higher education?
2. How do instructors vary their assessment strategies based on context (e.g., class size and course level) in online courses?
3. What modality and frequency do instructors use to provide feedback in online courses?
4. Are assessment types and strategies correlated with instructor characteristics in online courses?

Methods

Participants

One hundred and four instructors who taught online courses completed the survey. Seven instructors did not complete demographic information. There were 63.6% instructors ($n = 68$)

who identified as female, 26.2 % as male ($n = 28$), three preferred not to say, and one person reported *other*. For discipline, 36.4% of instructors were from Arts and Sciences and 28% were from Education. The respondents had different ranks: professors (17.8%), associate professors (15.9%), lecturers (15%), and assistant professors (13.1%). Respondents taught undergraduate (36.4%), graduate (21.5%), and a combination of both graduate and undergraduate (34.6%) courses. Their average age was 52.06. In terms of teaching experience, they had taught an average of 15.83 years in higher education and an average of 8.19 years online teaching experience. Only one participant reported being a novice instructor (1.0%), and eight instructors were advanced beginners (7.7%). Most participants indicated that they were competent ($n = 27$; 26.0%), proficient ($n = 36$; 34.6%), or expert ($n = 24$; 24.0%) in online teaching, whereas only a limited number of participants reported themselves as novice ($n = 1$; 1.0%) or advanced beginners ($n = 8$; 7.7%).

Survey

The research team conducted a thorough literature review to develop a survey with assessment types and strategies that instructors who teach online courses at higher education institutions use. The survey underwent a review of eight individuals who were instructed to review the categories and items, check items for clarity and appropriateness, and add or delete items. Expert panel participants included two research methodologists, two expert online instructors, and two senior instructional designers with several years of experience in higher education. Additionally, two advanced doctoral students provided feedback after reviewing the survey. The expert panel's feedback resulted in revisions of the rating scale, several scale items, and some demographic questions. The final survey had four sections with 43 questions.

The two categories included assessment types and assessment strategies, with 15 and 13 items, respectively. Items used a 5-point Likert-type scale with 1 = *not effective* to 5 = *extremely effective*. These items also included a *not used* response. Each category had an open-ended response question about other types and strategies used by respondents that were not listed. The third section included three questions pertaining to instructor feedback to students, and the fourth section included 10 questions on instructors' backgrounds and demographic information. One of those questions is an open-ended question asking instructors how their assessment strategies change based on course type (e.g., undergraduate vs. graduate; small class-size vs. large class-size).

Data Collection

Data was collected through two universities and one professional organization after institutional review board approvals were received at the researchers' participating institutions. Online surveys were distributed at one doctoral extensive and one doctoral intensive institution in the southeastern U.S. using internal email lists. Invitations for members of the professional organization were distributed through an email list and message boards. In total, 104 instructors completed the survey.

Data Analysis

Descriptive statistics including the mean and standard deviation were examined to answer the first and second research questions. Additionally, a frequency distribution was inspected to

grasp the overall tendency of the use of assessments and strategies used by instructors. The Spearman correlation coefficient was calculated to address the last research question, investigating the relationship between assessment types and strategies used by instructors and their characteristics. The instructors' demographic variables examined included: years of teaching in higher education, years of teaching online courses, age, and typical class size.

The three open-ended questions about assessment types and strategies, and context-based strategies were analyzed using open coding (Creswell, 2014; Creswell & Poth, 2018; Patton, 2015). Frequencies were used to develop categories based on codes that emerged. One of the researchers conducted the initial round of coding, using an inductive, manual approach to analyze responses to all three open-ended questions on assessment types, strategies and strategies based on context (course level and class size). When multiple codes emerged, categories were formed. The initial categories were presented and discussed with the other researchers in a collaborative team meeting. The team provided critical feedback which was used to refine category definitions. This iterative process strengthened the coding process.

Results

Effectiveness of Assessment Types

Participants were asked how effective a list of online types of assessments were to evaluate student learning. Table 1 shows the means and standard deviations of the studied types of assessment. The descriptive statistics are presented for each group—instructors primarily teaching undergraduates, graduates, and both—separately along with the entire sample group. For each group, the last column (*N*) indicates the number of participants responding to the effectiveness scale; the rest of the participants indicated they did not use that particular assessment type in their classes. As can be seen in Table 1, participants rated design projects, multimedia projects, and case study analysis consistently as very effective regardless of the level of courses they teach. However, it is worth noting that design projects were used by fewer than half of the participants ($n = 48$). By contrast, participating instructors tended to perceive self-directed assessments such as non-proctored exams ($M = 2.72$) and self-assessments ($M = 2.74$) least effective. It is interesting to note that quizzes were the most frequently used assessment tool ($n = 93$) but were not perceived to be very effective ($M = 2.99$), compared to the other types of assessments.

Table 1

Assessment Types (N = 104)

	<i>Total</i>		<i>Undergrad</i>		<i>Grad</i>		<i>Mix</i>	
Type of assessment	<i>M (SD)</i>	<i>N</i>	<i>M (SD)</i>	<i>n</i>	<i>M (SD)</i>	<i>n</i>	<i>M (SD)</i>	<i>n</i>
Writing assignments	3.68 (0.96)	92	3.64 (1.03)	33	3.84 (0.96)	19	3.69 (0.96)	35
Case study analysis	3.94 (0.78)	77	4.11 (0.64)	27	3.93 (0.70)	15	3.87 (0.86)	30
Quizzes	2.99 (0.98)	93	3.13 (0.91)	38	2.64 (1.28)	14	2.91 (0.95)	33
Exam (non-proctored)	2.72 (1.19)	74	2.93 (1.13)	29	2.75 (1.42)	12	2.41 (1.15)	27
Exam (proctored)	3.22 (1.33)	59	3.72 (1.18)	18	3.29 (1.70)	7	2.89 (1.22)	27

Multimedia project	4.03 (0.91)	79	4.00 (0.90)	28	3.94 (1.09)	17	4.27 (0.64)	30
Electronic portfolio	3.67 (1.11)	58	3.47 (1.36)	15	3.67 (1.29)	15	3.95 (0.84)	22
Design project	4.10 (0.83)	48	4.15 (0.69)	13	3.93 (1.21)	14	4.29 (0.47)	17
Student presentation	3.77 (0.88)	84	3.72 (1.00)	29	3.61 (0.98)	18	3.97 (0.74)	32
Reflection	3.23 (1.00)	69	3.17 (0.89)	23	3.63 (1.15)	16	3.12 (0.99)	26
Simulation	3.49 (1.14)	43	3.57 (1.02)	14	3.11 (1.76)	9	3.75 (0.86)	16
Educational online game	3.12 (1.06)	42	3.13 (0.96)	16	3.57 (1.13)	7	3.29 (0.99)	14
Self-assessment	2.74 (1.05)	61	3.21 (1.10)	24	2.50 (1.18)	10	2.38 (0.81)	21
Asynchronous participation	3.00 (1.08)	87	3.44 (1.08)	32	2.67 (0.84)	18	2.90 (1.11)	31
Synchronous participation	3.12 (1.10)	74	3.38 (1.17)	26	2.75 (1.14)	12	3.23 (0.94)	30

Note. The scale items range from 1 = *not effective* to 5 = *extremely effective*.

Other Effective Assessment Types

Participants were asked to respond to an open-ended question pertaining to effective types of online assessments they had used not listed in the survey. Fifty-five instructors completed this question. Eleven individuals indicated “none” or “not applicable,” whereas some listed types of assessment included in the survey. However, other respondents listed hands-on labs or at-home labs that students received via mail, ungraded checkpoints where students submit projects in stages, video analysis, discussion boards, interviews of professionals in the field, homework, computer-based homework, assessments through outside agencies, interactive polling, and oral exams.

Effectiveness of Assessment Strategies

Table 2 shows the means and standard deviations of the assessment strategies. Instructor-graded assignments ($M = 4.03$) and individual student assignments ($M = 4.02$) were the most common assessment strategies used and believed to be the most effective. Instructor-graded assignments were rated as most effective by instructors who teach only undergraduate courses and a combination of undergraduate and graduate courses, whereas individual student assignments were rated the most effective by instructors who teach only graduate students. Similar to assessment types, self-directed assignments such as ungraded assignments ($M = 2.53$) and peer feedback ($M = 2.89$) received the lowest ratings in terms of effectiveness.

Table 2

Assessment Strategies

	<i>Total</i>		<i>Undergrad</i>		<i>Grad</i>		<i>Mix</i>	
Assessment strategy	<i>M (SD)</i>	<i>N</i>	<i>M (SD)</i>	<i>n</i>	<i>M (SD)</i>	<i>n</i>	<i>M (SD)</i>	<i>n</i>
Individual student assignments	4.02 (0.70)	98	3.86 (0.68)	36	4.43 (0.68)	21	3.92 (0.65)	36

Group/collaborative project	3.02 (1.01)	89	3.13 (1.06)	31	3.00 (1.12)	20	2.94 (0.89)	34
Formative assessment	3.56 (0.92)	81	3.52 (1.00)	31	3.81 (1.17)	16	3.40 (0.89)	30
Summative assessment	3.58 (0.77)	86	3.45 (0.96)	31	3.78 (0.88)	18	3.63 (0.61)	32
Instructor graded assignment	4.03 (0.73)	101	3.92 (0.71)	38	4.10 (0.94)	21	4.11 (0.62)	36
Ungraded assignment	2.53 (1.22)	83	2.81 (1.64)	32	2.72 (1.07)	18	2.04 (1.06)	27
Automated graded assignment	3.13 (1.17)	79	2.94 (1.29)	33	3.08 (1.44)	13	3.29 (1.24)	28
Open book/notes assessments	3.35 (1.12)	78	3.18 (1.71)	28	3.67 (1.23)	15	3.40 (1.10)	30
Differentiated assignment	3.62 (1.01)	50	3.53 (1.26)	15	3.69 (0.95)	13	3.56 (0.92)	18
Peer feedback	2.89 (1.13)	74	2.75 (1.15)	24	3.00 (1.11)	19	2.89 (1.12)	27
Peer evaluations for collaborative assignment	2.97 (1.24)	65	2.95 (1.12)	21	3.06 (1.48)	18	2.95 (1.13)	22
Grading rubrics/criteria	3.75 (1.06)	93	3.71 (0.87)	34	3.90 (1.21)	20	3.79 (1.15)	34
Multiple attempts/submissions	3.44 (1.20)	80	3.42 (1.06)	33	3.94 (1.03)	17	3.12 (1.36)	25

Note. The scale items range from 1 = *not effective* to 5 = *extremely effective*.

Other Effective Assessment Strategies

The second open-ended question asked respondents to share other online assessments strategies used—not listed in the survey—that were effective. Only four instructors completed this question. Other participants reported they used flexible due dates, time-limited multiple choice exams, demonstrations, collaborative chats, and collaborative research assignments. Strategies that were erroneously listed by respondents as assessment types in the first open-ended question included: assignments following synchronous sessions, gamification, and problem-based learning.

Assessment Strategies Based on Context

The last open-ended question asked online instructors to provide details on how their online assessment strategies change based on context (e.g., course level, class-size). Of participating instructors, 86 responded to this question. For 11 individuals this question was not applicable because they only taught either undergraduate or graduate courses and either small or

large-sized courses. Five instructors made no changes based on either course level or class size. Tables 3 and 4 display the changes instructors make in their online courses based on context.

Table 3

Reported Strategy Changes Based on Course Level

Undergraduate-level courses	Graduate-level courses
Activities with formative feedback	Application-type assignments
Automated/auto-graded quizzes	Authentic assessments
Constant reminders	Choice in topics
Individual assessment	Co-design final products
More feedback sessions	Differentiation based on project goal/course type
More frequent assignments	Fewer assignments
More group work/projects	Fewer feedback sessions
More lower-stakes assignments	Fewer or no low-stake assignments
More scaffolding activities	Formative feedback
More smaller assessments	More experiential assignments
Reflections	More peer feedback
Vigilant about cheating: Use of Respondus Monitor and LockDown Browser	More written assignments
Worksheets	Open-ended assignments
	Peer help
	Peer reviews
	Portfolio-based assessments
	Practice
	Project-based assignments
	Quizzes
	Rich, detailed, direct feedback
	Rubric modification
	Scaffolded projects
	Small assignments within a project
	Take-home exams

Table 4*Reported Strategy Changes Based on Class Size*

Large classes	Small classes
Additional faculty to provide open-ended feedback	Deeper assessments with nuanced feedback
Assignments graded by preceptor and instructor	Discussion boards
Automated assessment forms	Fewer group projects
Change of numbers of problems assigned in class	Individual assessments
Discussion boards	Larger assessments
Comprehension activities	Low-stakes formative assessments
Group assignments/projects/activities	More assessments
Fewer essays	More grading by professor
Fewer large assignments	More in-depth writing assignments
Forum-based questions	More manual feedback
Less individualized/personalized feedback	More written assignments
Low stakes grading of written assignments	Projects with individualized feedback
More automated feedback	Scaffolded course project with feedback 3–4 times
More automated grading	Show critical thinking
More collaborative assignments	Written assignments with meaningful feedback
More online grading	
Random in-depth grading	
Smaller assignments with less feedback	
Small groups	
Whole-class or generalized feedback	

Modality and Frequency of Feedback

Table 5 presents the distributions of the modality and frequency of instructors' feedback. The majority of the participants used texts to provide feedback ($n = 95$; 88.8%). Approximately one fifth of instructors used audio as the feedback modality ($n = 21$; 19.6%). In terms of the frequency of the feedback, over two thirds of the participants indicated that they provide feedback within a week ($n = 78$; 72.9%).

Table 5*Modality and Frequency of Feedback*

Variable	<i>n</i> (%)
Modality for feedback	
Text	95 (88.8%)
Audio	21 (19.6%)
Video	17 (15.9%)
Feedback frequency	
Within one month	1 (0.9%)
Within one week	78 (72.9%)
Within one day	17 (15.9%)
Immediately	6 (5.6%)
Missing	5 (4.7%)

Instructors' Characteristics

The Spearman correlations showed a significant negative relationship between instructors' years of teaching in higher education and multiple attempts/submission strategy ($r = -0.249, p = .030, n = 76$). By contrast, instructors with more online teaching experience perceived peer evaluations for collaborative assignments as more effective, $r = 0.271, p = .33, n = 62$.

Age was found to be one of the factors that are associated with various types of assessments. Age showed positive relationships with writing assignments ($r = 0.328, p = .002, n = 86$), non-proctored exams ($r = 0.286, p = .013, n = 67$), proctored exams ($r = 0.347, p = .013, n = 51$), multimedia project ($r = 0.258, p = .026, n = 75$), and student presentations ($r = 0.223, p = .043, n = 78$). Finally, class size was negatively correlated with individual student assignments, $r = -0.300, p = .004, n = 90$.

Discussion

This study examines online instructors' perception of the effectiveness of various assessment types and strategies. Although many of these assessments have been used for decades, only few studies have investigated the effectiveness of various types of assessments and strategies in online courses. Additionally, examining assessment strategies based on context such as course level (undergraduate vs. graduate) and class size (small vs. large) adds valuable insights to the literature on online learning. The study also addresses feedback modalities and frequency, both of which are critical components of effective online teaching. Finally, analyzing the relationship between instructor characteristics and assessment types and strategies offers guidance to online instructors. Overall, the study offers practical implications for improving assessment practices in online education.

Most Effective Assessments

Our respondents perceived design projects and multimedia projects as most effective among the assessment types regardless of level of courses they taught. Authentic assessments such as design and multimedia projects apply to real-world situations or scenarios where learners create a product or artifact, therefore demonstrating their knowledge and abilities in new situations, scenarios or problems (Dabbagh & Bannan-Ritland, 2005). It is interesting to note, however, that design projects were used by fewer than half of the participants. Other types that were rated highly were case study analysis and student presentations. These types of assessments allow students to actively analyze and evaluate newly acquired knowledge and apply it to a practical situation.

Online instructors perceived instructor-graded assignments and individual student assignments to be the most effective assessment strategies. Instructor graded assignments were rated the highest by instructors who teach undergraduate courses and combination of undergraduate and graduate students in comparison to ungraded and automated-graded assignments. This shows that instructors believe students value the grading they perform. Also, individual student assignments were rated the most effective by instructors who teach graduate students. Graduate students are usually working adults with families and busy schedules and consider it less difficult to work on assignments individually rather than in a team due to the challenges group assignments may present (LaBeouf et al., 2016).

Least Effective Assessments

In this study, online instructors tended to perceive self- assessments and non-proctored exams to be least effective. Students in online courses tend to complete more graded activities compared to self-assessments because they may not have sufficient time to work on non-graded assignments. Moskal (2010) pointed out that when self-assessments are administered in isolation it is incomplete. Additionally, online instructors perceived non-proctored exams to be less effective compared to proctored exams. Instructors may perceive that non-proctored exams may not be valid when learners are allowed to use notes or other resources to demonstrate their knowledge or skill.

Results indicate that respondents perceived ungraded assignments and peer feedback as not very effective strategies. Similarly to self-assessments, learners may not take the time to complete ungraded assignments because these assessments have no impact on their grades. Some instructors may not use peer feedback because they do not see value in peers providing feedback to others. It is also possible that learners are not adequately prepared to provide meaningful feedback to other learners. Peer feedback only adds value when there is structure and students are trained on how to provide meaningful feedback in the peer review process (Kearns, 2012).

Assessment Strategies Based on Context

Many of our participants taught a mix of undergraduate and graduate courses, in addition to small and large classes. This is likely the case for many instructors who teach at higher education institutions. Some instructors chose not to make adjustments when teaching different course types; however, many instructors who taught graduate courses or small classes used strategies to provide scaffolding such as formative feedback or more detailed feedback. Others used differentiation strategies such as more open-ended assignments, portfolios or they gave

learners the option of choosing topics. Some also involved peers in the feedback cycle, such as peer help, reviews, and feedback. Lydel (2008) pointed out that ongoing reform in graduate education includes issues such as quality measures, student-centered approaches, and learner empowerment. Other strategies provided included reducing the number of assignments and integrating authentic or application-based assessments.

Instructors who taught primarily undergraduate courses or large classes used more frequent, smaller, and low-stakes assessments. Moore and Kearsley (2012) point out that learners are more likely to finish an online course when they complete assignments more frequently. Instructors used automated grading of quizzes and tests to provide immediate feedback to students, a strategy mentioned by Simonson et al. (2012). To reduce their workload, they increased the number of group projects as suggested by Dunlap (2007). Additionally, they used more reminders and feedback sessions to scaffold student learning.

Instructor Feedback

Most respondents used text to provide feedback whereas one-fifth of instructors used audio as the feedback modality. Cavanaugh and Song (2014) point out that most online instructors use text to provide feedback to learners. Results of their study showed that most instructors preferred providing written feedback due to technical issues and concerns about clarity of their feedback. Mulliner and Tucker (2017) found that 92% thought typed feedback was either *very* or *quite* effective, whereas 61% of participating instructors rated audio feedback to individual students as effective.

In terms of the frequency of the feedback, over two-thirds of the participants indicated that they provide feedback within a week, whereas about one-tenth of the participants reported providing feedback within a day. Exemplary or award-winning online instructors who were interviewed provided grades and feedback within two to five days (Lewis & Abdul-Hamid, 2006; Martin et al., 2019). Timeliness is an important aspect of the feedback process according to the literature. Prompt feedback is not only important for student learning but also to demonstrate instructor presence, facilitate interaction, and increase learner satisfaction (Chickering & Gamson, 1987; Gaytan & McEwen, 2007; Lee, 2014; Lewis & Abdul-Hamid, 2006; Martin et al., 2019).

Instructor Characteristics

Results show that instructors' teaching experience in higher education resulted in a negative correlation with multiple submission attempts. This suggests that as instructors gain more teaching experience, they tend to see the multiple attempts/submission strategy less effective. Davis et al. (2020) found that an unlimited number of attempts on quizzes improved students' outcomes on exams overall. However, students who were provided with formative feedback on essays did not have significantly higher grades. Hence, the effectiveness of this strategy is questionable, particularly because it can be time consuming for instructors (Crisp, 2007). It is possible that instructors become disillusioned with this strategy over time because they may not believe that students use their feedback.

In contrast, online teaching experience was positively correlated with peer evaluations for collaborative assignments. As online teaching experience increases, instructors find peer

evaluations more effective. Some instructors, however, question the quality and effectiveness of peer evaluations. Sprague et al. (2019) found that most students agreed with the scores they provided for group members, and these results support the use of peer evaluations. Instructors may see the relevance of peer evaluation use as they gain online teaching experience.

Limitations

The reader should be aware of some limitations. First, the study was geographically limited. Second, the majority of respondents taught in either arts and sciences or education. Future research may focus on instructors who teach in other disciplines. Third, the sample size was relatively small. Fourth, the data is self-reported due to the nature of the study. Fifth, some participants may not have been as forthcoming as others about their assessment practices due to social desirability. Last, those who completed the survey were volunteers who may have held views differently from those individuals who did not participate in the study.

Implications for Research and Practice

Future research may be conducted by selecting research sites in multiple states, regions, or countries. The study may be replicated by including multiple sites in the data collection plan. Researchers could also examine learners' perceptions of effectiveness of online assessments, particularly attitudes and opinions pertaining to individual and group assignments, peer feedback and review, and authentic assessments.

The findings from this study also have implications for practitioners. Online instructors can review the various assessment types and strategies and adopt the ones that might be more effective for the student level and class size they teach. Similarly, instructional designers can provide guidance to instructors regarding assessment types, strategies, and feedback mechanisms. Overall, students will benefit when their instructors use varied assessment types and strategies that are appropriate for the courses they teach.

Conclusion

The purpose of the study was to investigate higher education instructors' perceptions of effectiveness of assessment types and strategies in online learning environments. Participants rated assessment types and strategies from not effective to very effective in addition to providing readers with types and strategies not included in the survey. Additionally, participating instructors revealed how they change their strategies based on context and how they provide feedback in terms of frequency and modality. Results of this study can provide practitioners, administrators, and researchers with an understanding of how online instructors currently assess student learning and performance. They also give a broad overview of assessment types and strategies that may be used in online environments by instructors.

Learners should have an opportunity to demonstrate their newly acquired knowledge and/or skills in multiple formats (Gaytan & McEwen, 2007). Educators and administrators need to ask themselves what assessments are necessary, how to measure learning outcomes effectively and fairly, and how to assess critical thinking and problem solving in different environments and

contexts (Robles & Braathen, 2002). This becomes an even more important issue as more learners in higher education study in online learning environments.

Declarations

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Ethics Approval

The authors assert that approval was obtained from the ethics review boards at North Carolina State University and the University of North Carolina at Charlotte.

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Quantitative Investigation: Neuromyths, Knowledge About the Brain, Evidence-Based Practices, and Professional Development in Higher Education

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Abstract

Shifting student demographics, evolving economic conditions, and the rapid advancement of artificial intelligence are prompting institutions to reconsider established pedagogical models and professional development. This study is the first phase of a two-year explanatory sequential mixed-methods project. A total of 303 individuals completed the survey, including instructors, instructional designers, and professional development administrators, representing primarily four-year and two-year institutions and other institutions such as health sciences centers, medical institutions, and online management programs. This study reports on participants' level of awareness of neuromyths, general knowledge about the brain, knowledge about the brain and learning, and evidence-based practices among instructors, instructional designers, and professional development administrators who worked across online, hybrid, HyFlex, and onsite modalities. The study compares mean percentages of accurate responses between groups and factors associated with awareness using Analysis of Variance (ANOVA) and post-hoc statistical tests. The study reports on strategies, principles, and practices used by participants to support learning. Additionally, the study reports on

participants' perceived value and interest in learning more about scientific knowledge about the brain. Although participants demonstrated high levels of awareness regarding the brain, knowledge about the brain and learning, and evidence-based practices, the results also revealed opportunities to increase awareness about neuromyths and scientific knowledge about the brain to support learning. This study provides critical insights into opportunities for enhanced awareness and transformative educational practices through professional development.

Keywords: Neuromyths, evidence-based practices, professional development, higher education, instructors, instructional designers

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The higher education landscape continues to shift in the United States (U.S.). Compounding factors have impacted enrollment patterns, including the looming enrollment cliff with projected decreases in college applications due to declining birth rates and demographic shifts (Hofman, 2025; Hoover, 2024; Marcus, 2025;), increasing questions about the value of a higher education degree (Merisotis, 2025; Mowreader, 2024), and high cost of tuition (Brown, 2025; Petersen, 2024; Wood, 2024). As further noted by Wartham (2025), “Institutions are now expected to be dynamic engines of workforce readiness—equipping learners with not just knowledge, but the agility and skills necessary to thrive in a world defined by continuous change” (para. 1). To address these challenges and support upskilling, reskilling, and career advancement, professional development for faculty and instructional designers is essential to support student engagement, increase retention, and prepare graduates to thrive in an increasingly complex global workforce.

Effective professional development is essential to the facilitation of effective teaching and learning experiences in contemporary higher education. One underlying factor is the historical lack of required pedagogical training since higher education faculty have disciplinary expertise and training in research, but may not have formal pedagogical preparation (Baker, 2024; Darling-Hammond, 2021; Gould & Hammond, 2021; Silander & Stigmar, 2021). Prior to the COVID-19 pandemic, professional development supported traditional on-campus programs and expanding online programs across higher education institutions (HEIs). During the pandemic, professional development became even more essential as courses quickly pivoted from on-campus learning to remote learning. To support the national shift in teaching modality, the United States federal government provided \$39.6 billion in Higher Education Emergency Relief Funds (HEERF) to serve students and to ensure learning continued during the pandemic as instruction shifted online (United States Department of Education, 2023). After the initial shift to emergency remote instruction in early 2020, many HEIs continued to sustain their remote and hybrid learning infrastructure utilizing HEERF (Strietelmeier, 2023). Following the pandemic, HEIs have continued to offer professional development to support teaching and learning across modalities.

This study investigated professional development engagement of instructors, instructional designers, and professional development administrators working within four-year and two-year HEIs. Specifically, the study focused on the level of awareness of neuromyths, general knowledge about the brain, knowledge about the brain and learning, evidence-based practices, and interest in scientific knowledge about the brain to support learning.

Literature Review

The literature review begins by examining research studies on neuromyths, general knowledge about the brain and learning, and evidence-based practices. The literature review then explores professional development and its importance to teaching, learning, and retention.

Neuromyths

Neuromyths are false beliefs related to misconceptions, misunderstandings, or misinterpretations about the brain and brain function often associated with education and learning. Advancements in research and brain imaging technology have challenged these widespread beliefs about the brain and learning. Some of the most “classic” and prevalent neuromyths include: (a) some individuals are “left-brained” and some are “right-brained,” and this helps explain differences in learning (OECD, 2002; Tokuhamma-Espinosa, 2018); (b)

individuals use only 10% of the brain (Bruer, 1997; OECD, 2007; Tokuhamma-Espinosa, 2018); (c) it is best for children to learn their native language before a second language is learned (OECD, 2007; Tokuhamma-Espinosa, 2018); (d) there are critical periods in human development after which certain skills can no longer be learned (Bruer, 1997; OECD, 2007; Tokuhamma-Espinosa, 2018); (e) learning problems associated with developmental differences in brain function cannot be improved by education (Bruer, 1997; Goswami, 2006; OECD, 2007; Tokuhamma-Espinosa, 2018); and (f) individuals learn better when they receive information in their preferred learning styles (OECD, 2007; Pashler et al., 2008; Riener & Willingham, 2010; Tokuhamma-Espinosa, 2018; Weale, 2017).

The past three decades have seen increasing research on the awareness of neuromyths among educators. While most studies have been conducted within PK-12 education with pre-service and in-service teachers, increased research has been conducted in higher education. Within PK-12 education, studies have found that pre-service teachers and teachers benefit from initiatives aimed at enhancing neuroscience education literacy in both the initial education and continuous professional development (Bei et al., 2023; Jørgensen et al., 2023; McMahon et al., 2019).

Within higher education, there has been a growing number of related studies. Macdonald and colleagues (2017) examined endorsement of neuromyth beliefs in a U.S. sample of educators ($n = 598$), individuals with high neuroscience exposure ($n = 234$), and the general public ($n = 3,045$), analyzing predictors of individual differences in neuromyth endorsement. In their study, they found seven neuromyths that factored together (items on learning styles, dyslexia, the Mozart effect, the impact of sugar on attention, right-brain/left-brain learners, and using 10% of the brain). Their findings revealed that the general public endorsed the greatest number of neuromyths ($M = 68\%$), followed by educators ($M = 56\%$), and individuals with neuroscience exposure ($M = 46\%$). Learning styles and dyslexia were the two most endorsed neuromyths across all groups. For example, the dyslexia myth of “seeing letters backwards” was endorsed at high rates among the public ($M = 76\%$), educators ($M = 59\%$), and even those with high neuroscience exposure ($M = 50\%$). The study also indicated greater accuracy on neuromyths was predicted by (a) age (being younger), (b) education (having a graduate degree), (c) exposure to neuroscience courses, and (d) exposure to peer-reviewed science (Macdonald et al. 2017).

In 2018, the Online Learning Consortium conducted a study of higher education professionals, surveying 1,290 participants, including full-time instructors (33%), part-time instructors (13%), instructional designers (26%), professional development administrators (18%; $n = 172$), and other educational roles (10%) (Betts et al., 2019). Additional studies (Fragkaki et al., 2022; see reviews by Rousseau, 2021 and Torrijos-Muelas et al., 2021) have included higher education students and faculty. In these studies, the findings revealed an opportunity to increase the level of awareness regarding neuromyths to support student academic success. Understanding educator awareness of neuromyths in PK-12 education and higher education is important so professional development can share resources and training to address the persistence of neuromyths (Grospietsch & Mayer, 2020; Williams et al., 2025) and support evidence-based practices.

Researchers have called on future studies to address the impact of neuromyths on teaching practices and learner outcomes, and to focus on prevention strategies (Hughes et al., 2022; Taylor & Kowalski, 2023). Prevention strategies include refutational teaching (Guzzetti et al., 1993; Will et al., 2019), which involves the use of refutational texts and

lectures to confront and correct misconceptions. This approach has been reported to lead to significantly reduced misconceptions in both science (Will et al., 2019) and psychology (Kowalski & Taylor, 2009; Taylor & Kowalski, 2012). For example, in the case of the dyslexia myth (backwards reading), refutational text strategies have been used to examine and address preservice teachers' concepts of dyslexia, finding that dyslexia knowledge could improve through reading refutation text as compared to control text (Peltier et al., 2020, 2022). Another strategy to prevent neuromyths involves the use of think-aloud protocols with students to better understand and address their sources of misconception, which supports instructors in utilizing refutational texts and lectures in teaching and learning contexts, as it has been established that misconceptions are more intractable than a lack of knowledge on a particular topic (Taylor & Kowalski, 2012). Other strategies include addressing the role of confidence in adherence to false beliefs, along with perceived sources of information in adherence to neuromyths (Hughes et al., 2022). Strategies for professional development include ensuring requisite topic depth and focus (i.e., to address conceptual change rather than myth adherence).

As the literature on neuromyths continues to grow (Betts 2019; Dekker et al., 2012; Geake, 2008; Macdonald et al., 2017; Pasquinelli, 2012; Bei et al., 2023; Tsang, 2024; Tunga & Çağıltay, 2023), researchers have identified that integrating insights from education, psychology, and neuroscience into professional development is an important strategy for increasing awareness and refuting neuromyths (Anderson, 2021; Mason, 2009; Pasquinelli, 2013). Researchers contend that scientifically based understandings are more likely to result in adoption and application to practice through bidirectional and ongoing coursework in educational neuroscience, such as in the case of dyslexia, by including neurocognitive and linguistic processes involved in reading development, as identified by advocates in the field (e.g., Consortium on Reading Excellence in Education, International Dyslexia Association) (Anderson, 2021).

General Knowledge about the Brain and Learning

There has been an increased focus on the integration of educational neuroscience into professional development (Chang et al., 2021; Dubinsky et al., 2013; Hachem et al., 2022; Pradeep et al., 2024; Tan & Amiel, 2019). Studies have examined the impact of professional development on general knowledge about the brain and learning, including basic neuroanatomical structures and functions (Chang et al., 2021), neuroplasticity (Dubinsky et al., 2013), and how factors like emotions, context, and attention can facilitate or inhibit knowledge acquisition. One of the key challenges of integrating educational neuroscience concepts into professional development for educators is helping non-neuroscientist educators make sense of complex neuroscience terms and processes. This applies to instructors at both the PK-12 and post-secondary levels. A study by Tan and Amiel (2019) found that instructional metaphors in K-12 professional development helped deepen teacher understanding of educational neuroscience concepts when applied in practice. Hachem and colleagues (2022) designed and delivered a year-long professional development program in partnership with a high school in Western Canada. Teachers involved in the program described how neuroscience knowledge acquired during professional development training helped improve their relationships with students over time. Cui and Zhang (2021) surveyed K-12 teachers (n=214) and found that neuroscience professional development was correlated with a higher knowledge of neuroscience concepts.

A separate study of higher education instructors by Chang and colleagues (2021) followed up with participants one year after they completed a three-week course that

emphasized foundational ideas in educational neuroscience. The authors found that participants perceived all educational neuroscience concepts introduced in the course to be relevant, and multiple concepts actively served as guiding principles in pedagogy and instructional design. Notably, the study focused on participant implementation of educational neuroscience concepts and did not measure student outcomes (Chang et al., 2021, p. 13). The increasing number of studies exploring the impact of professional development aimed at strengthening instructors' awareness and/or praxis of concepts grounded in cognitive psychology, education, and neuroscience reflects the continuing efforts to bridge the gap between educational research and practice.

Evidence-Based Practices

Buskist and Groccia (2011) define evidence-based teaching as “the conscientious, explicit, and judicious integration of best available research on teaching technique and expertise within the context of student, teacher, department, college, university, and community characteristics” (p. 8). They offer example practices such as formative assessment/quizzing for mastery, alternating short periods of lecture with in-class active learning exercises, and team projects involving applied or realistic problem solving (Buskist & Groccia, 2011; also see Jakobsen & Daniel, 2019). A wide variety of benefits of these kinds of practices have been documented within higher education classrooms, including improvements to grades, reduction of disparities affecting less advantaged and minoritized students (Pennebaker et al., 2013; Penner et al., 2021), and even reduced anxiety among students (Cooper et al., 2018).

Evidence-based practices are dynamic and continuously evolve through research and new discoveries. Recent research, for example, has strengthened the understanding of the effectiveness of retrieval practice or retrieval-based learning, meaning answering test questions (as one would do with a low-stakes quiz over assigned reading, for example) as part of the learning or study process (Butler & Roediger, 2007; Carpenter et al., 2022; Dunlosky & O'Brien, 2022; Karpicke & Roediger, 2008; Miller, 2011; Yang et al., 2023). Spacing of study is another core practice for building knowledge quickly; this well-established principle holds that study sessions increase in effectiveness as they are more widely spaced in time, even when the total amount of study time remains constant (Carpenter et al., 2022; Feenstra et al., 2024; Carpenter et al., 2012; Dunlosky & O'Brien, 2022).

Evidence-based practices may not always be obvious or intuitive to faculty. Even those who are interested in innovation may lack the training or background knowledge to select instructional techniques backed by research, as well as the time to read extensively within the field of learning sciences (Lovett et al., 2023; Wynants & Dennis, 2018). It follows that deliberate cultivation of knowledge and skill in evidence-based teaching is needed for most faculty, along with supports to make this feasible to accomplish given constraints on faculty time. In contemporary institutions of higher education, professional development is a critical mechanism for developing and disseminating evidence-based teaching practices. Teaching and learning centers are places where faculty can both learn about the relevant research and gain guidance about how to put it into practice in their own classes (Lovett et al., 2023). Leaders of these centers, along with associated professionals such as instructional designers, therefore, have an important role to play in identifying, disseminating, and implementing evidence-based practice throughout a campus.

Professional Development

Professional development is defined as “structured professional learning that results in changes in teacher practices and improvements in student learning outcomes” (Darling-Hammond et al., 2017, p. v). Professional development includes, but is not limited to, onboarding, workshops, webinars, bootcamps, and certificate programs. Prior to the pandemic, many HEIs offered professional development on campus. However, the higher education landscape quickly shifted during the pandemic. By mid-April 2020, “192 countries had closed all schools and universities, affecting more than 90 percent of the world’s learners” (Psacharopoulos et al., 2020, para. 1). As HEIs closed, professional development moved to online, hybrid, and HyFlex formats to ensure learning continued throughout the pandemic.

The impact of the pandemic on higher education enrollments was profound. Nationally, undergraduate enrollments dropped approximately 8% from 2019 to 2022, with continued declines even after HEIs returned to in-person classes (Binkley, 2023; Shapiro, 2023). Although undergraduate enrollments in fall 2023 grew for the first time since the beginning of the pandemic, the sudden and prolonged decreases in enrollments due to the pandemic greatly impacted many institutions (National Student Clearing House, 2024). Since March 2020, “at least 83 public and nonprofit colleges have closed, merged, or announced closures or mergers” (Castillo & Welding, 2025, para. 1). In December 2024, the Federal Reserve Bank of Philadelphia issued a report predicting that up to 80 colleges may close in the next five years with the upcoming demographic cliff (Kelchen et al., 2025). In September 2025, it was reported that hundreds of U.S. colleges could be poised to close in the next decade (Rembert & Albright, 2025).

In this challenging landscape, professional development for faculty and instructional designers is more important than ever for HEIs to support and retain the students they enroll, now across multiple modalities. Research studies have frequently documented relationships between teaching quality and student retention across postsecondary contexts (Arce et al., 2015; Mestan, 2016; Qvortrup & Lykkegaard, 2022), among other non-teaching factors. Effective professional development can improve teaching quality (Fabriz et al., 2020; Gore et al., 2017), though impact varies considerably. When professional development programming is ineffective, this may reflect issues related to program duration, insufficient administrative support for integration of new knowledge, or a lack of alignment with classroom needs (Zhou et al., 2025). Sims et al. (2025) propose that effective professional development succeeds through a combination of four components: it develops teacher insights, motivates change, facilitates the development of techniques, and supports the integration of those techniques in practice. The integration of translational research from neuroscience, psychology, and education provides new insight that builds upon evidence-based practices for teaching and supports the transfer of learning. Studies using brain imaging techniques exploring the human learning process further support evidence-based practices while debunking classical neuromyths, such as using just 10% of the brain, being right or left-brained, and visual-auditory-kinesthetic learning styles (Betts et al., 2019). By leveraging research from neuroscience, psychology, and education in professional development offerings, faculty and instructional designers can participate in training that supports teaching, learning, and assessment across all course modalities to support student engagement, retention, and completion.

Despite the growing body of research on neuromyths and evidence-based practices, most studies have centered on PK–12 contexts, with comparatively fewer focusing on higher

education faculty, instructional designers, and professional development administrators. Moreover, while awareness of neuromyths and the application of learning sciences are increasing, persistent misconceptions and uneven implementation of evidence-based strategies suggest critical gaps in knowledge translation and professional development. To address these gaps, the present study builds on prior research by examining the awareness levels, practices, and professional learning interests of key stakeholders in higher education.

The Present Study

This study is the first phase of a two-year international explanatory sequential mixed-methods research project. The first part of this project was a quantitative study designed to examine the awareness of neuromyths, general knowledge about the brain, knowledge about the brain and learning, and evidence-based practices among instructors, instructional designers, and professional development administrators who work across online, hybrid, HyFlex, and onsite modalities. The second part of this project, which was informed by this study, was a qualitative study that included focus groups with the data being reported in a separate article.

This comprehensive quantitative study builds upon prior research conducted on neuromyths and evidence-based practices through the Online Learning Consortium (Betts et al., 2019) as well as other national and international studies (Dekker et al., 2012; Dündar & Gündüz, 2016; Fragkaki et al., 2022; Macdonald et al., 2017). Additionally, this study provides new insight into the types of strategies, principles, and practices being applied to support learning and what instructors, instructional designers, and professional development administrators would like to learn more about. The data collected from this study were used to support the questions designed for the second phase of this mixed-methods study that explored professional development attended post-pandemic.

Four research questions guided this study.

What was the level of awareness of neuromyths, general knowledge about the brain, knowledge about the brain and learning, and evidence-based practices among professional roles (instructor, instructional designer, professional development administrator)

Were there statistically significant differences between instructors, instructional designers, and professional development administrators in awareness of neuromyths, general knowledge about the brain, knowledge about the brain and learning, and evidence-based practices?

What types of strategies, principles, and practices did instructors, instructional designers, and professional development administrators apply to support learning?

To what extent was there interest in instructors, instructional designers and professional development administrators in scientific knowledge about the brain?

Method

Research Design and Participants

The instrument used for this study builds upon the prior survey used in 2018 for an Online Learning Consortium (OLC) international study (Betts et al., 2019). Small changes

were made to the 2018 study for greater consistency with wording, such as using third-person pronouns and not mixing second- and third-person pronouns throughout. There were five sections for this study: (a) General Statements about the Brain; (b) General Statements about Teaching, Learning, and Assessment; (c) Instructional Practices; (d) Professional Development; and (e) Demographics and Professional Background. For the first two sections, participants were provided with a list of statements from which they selected three choices: *correct*, *incorrect*, and *unsure*. The third section provided a detailed list of evidence-based instructional strategies, principles, and practices that support learning. Participants were asked to identify whether they were familiar with them and how they learned about them. The fourth section asked participants about the types of professional development they attended during the pandemic. Additionally, they were asked about their interest in scientific knowledge about the brain and whether they found it to be valuable to their teaching practice, course development, and professional development. The fifth section asked questions regarding the participants' role (instructor, instructional designer, professional development administrator, other) and the type of institution in which they taught, with the location of the institution. Additional information was asked regarding the types of courses taught or designed prior to the pandemic, course format preference for teaching and instructional design, gender, highest degree completed, and whether they completed the 2018 OLC survey.

Convenience and snowball sampling were used for this study. Survey collection occurred between October 2021 and January 2022. An invitation was sent through the OLC listserv inviting members to complete an online survey and to share the invitation with others who were in the roles of instructor, instructional designer, and administrator responsible for professional development. The OLC sent out the first invitation with one email reminder. Members of the research team also shared the email invitation with peers at HEIs nationally and internationally. Recipients were asked to forward the invitation to other eligible participants. Because the survey invitation was disseminated through multiple channels and sharing was at the discretion of the recipients, a response rate could not be calculated.

This study was approved by the Institutional Review Board (IRB) at Drexel University. The invitation included a description of the study, definitions, and an embedded link to the Qualtrics survey site. Participants had to give informed consent before completing the survey. Statistical Package for the Social Sciences (SPSS for Windows, ver. 29) was used to analyze the data. Frequencies and cross-tabulations were used to present descriptive data. Inferential statistics included one-way Analysis of Variance (ANOVA) for multiple comparison tests to evaluate differences among the three professional groups (instructor, instructional designer, professional development administrator) on mean for percent accurate responses to questions about neuromyths, general statements about the brain, and knowledge about the brain and learning ($[\# \text{ of correct responses to } 27 \text{ questions} / 27] * 100\%$). One-way ANOVA was also used to evaluate differences among the three professional groups on mean for percent accurate responses to questions about evidence-based practices ($[\# \text{ of correct responses to } 23 \text{ questions} / 23] * 100\%$). For all statistical analyses, the level of significance was set at $\alpha = 0.05$. Post-hoc analysis using the Bonferroni test was conducted to examine the differences in the mean scores between the groups. The Cronbach's alpha coefficient was .711 for the 27 neuromyths, general statements about the brain, and knowledge about the brain and learning items, and .614 for the 23 evidence-based practices items, which revealed an acceptable level of internal consistency.

Participants

A total of 303 individuals participated in the study and completed the survey. All participants provided informed consent. Of the participants, approximately half were instructors (49%), including full-time and part-time instructors. Thirty-three percent were instructional designers, and 18% were professional development administrators. Most participants (71%) worked in four-year institutions while 17% worked in two-year institutions and 12% worked in other types of institutions of which some of the responses included a health sciences center, medical institution, and online management program. Fifty-nine percent of the participants worked at public institutions followed by private institutions (35%), for-profit institutions (3%), and other types (3%) of which only four responses were listed including the federal government, military, non-profit, and military graduation institution. Participants reported they were currently teaching and engaged in course development across undergraduate programs, graduate programs, and professional certificates/certification programs. The data revealed that 25% of participants taught across multiple types of programs while 39% were engaged in course development across multiple types of programs. Of the participants, 21% shared that they did not teach while 12% did not develop courses.

Fourteen percent of participants completed the 2018 OLC survey that examined neuromyths, general knowledge about the brain, and evidence-based practices. Table 1 includes data regarding role, institution (level, type), and teaching and course development experience.

Table 1

Role, Type of Institution, and Experience

Role	<i>n</i>	%
Instructor (faculty, lecturer, professor) full-time (n=104)	146	49
part-time (n=42)		
Instructional designer	97	33
Administrator (PD)	54	18
Total	297	100
Institution: Level	<i>n</i>	%
2-Year institution	50	17
4-Year institution	209	71
Other	35	12
Total	294	100
Institution: Type	<i>n</i>	%
Public	174	59
Private	105	35
For-profit	8	3
Other	9	3
Total	296	100
Teaching Across Programs	<i>n</i>	%
Only associate's degree	28	9.3
Only bachelor's degree	65	21.7
Only graduate (master's, doctoral) degree	40	13.3
Only professional certificates/certifications	9	3.0

Associate and bachelor's degrees	12	4.0
Associate and graduate degrees	2	.7
Associate degree and professional certificate/certifications	4	1.3
Associate, bachelor's, and graduate degrees	5	1.7
Associate, bachelor's, and professional certificate/certifications	2	.7
Bachelor's and graduate degrees	23	7.7
Bachelor's and certificate/certifications	2	.7
Bachelor's, graduate degree, and professional certificate/certifications	14	4.7
Graduate degree and professional certificate/certifications	11	3.7
Other	21	7.0
I don't teach	62	20.7
Total	300	100.0
Course Development Across Programs		
	<i>n</i>	<i>%</i>
Only associate's degree	31	10.3
Only bachelor's degree	51	17.0
Only graduate (master's, doctoral) degree	34	11.3
Only professional certificates/certifications	19	6.3
Associate and bachelor's degrees	6	2.0
Associate and graduate degrees	2	.7
Associate's degree and professional certificate/certifications	2	.7
Associate, bachelor's, and graduate degrees	7	2.3
Associate's, bachelor's, and professional certificate/certifications	2	.7
Associate, graduate, and professional certificate/certifications	2	.7
Associate, bachelor's, and professional certificate/certifications	12	4.0
Bachelor's and graduate degrees	37	12.3
Bachelor's and certificate/certifications	4	1.3
Bachelor's, graduate degree, and professional certificate/certifications	28	9.3
Graduate degree and professional certificate/certifications	16	5.3
Other	10	3.3
I don't develop courses	37	12.3
Total	300	100.0

Most participants self-identified as female (71%). Twenty-five percent self-identified as male, 1% self-identified as non-binary, and 3% chose not to respond. The age of participants at the time of the survey showed that most were between the ages of 45 to 54 years old (29.8%), 55 to 64 years old (26.6%), and 35 to 44 years old (23.2%). The highest degree completed by participants were doctorate degree (46.3%) including PhD (35%) and EdD (11.3%) followed by master's degree (44%). Table 2 includes a breakdown of demographics.

Table 2

Demographics

Gender	<i>n</i>	<i>%</i>
Female	212	71
Male	74	25
Non-binary	2	1

I choose not to respond	11	3
Total	299	100
Age at Time of Survey	<i>n</i>	%
18 to 24 years	2	0.7
25 to 34 years	31	10.7
35 to 44 years	67	23.2
45 to 54 years	86	29.8
55 to 64 years	77	26.6
65 years or older	21	7.3
I choose not to respond	5	1.7
Total	289	100
Highest Degree Completed	<i>n</i>	%
Bachelor's degree	4	1.3
Completed some postgraduate	2	0.7
Master's degree	132	44
PhD (Doctor of Philosophy)	105	35
EdD (Doctor of Education)	34	11.4
DBA (Doctor of Business)	4	1.3
Administration		
JD (Juris Doctor)	2	0.7
MD (Doctor of Medicine)	1	0.3
Other	16	5.3
Total	300	100

Participants represented 22 countries across six continents including North America, Europe, Asia, the Middle East, Africa, and Oceania. Of US participants, a total of 43 states and Washington, DC were represented. Table 3 includes a breakdown of the countries in which the participants' institution was located.

Participants were asked to rank their level of preference in modalities for teaching and instructional design with 1 being the most preferred to 4 being the least preferred. Online was selected by Instructional Designers and Professional Development Administrators as their preferred teaching modality while Instructors selected Onsite (see Table 3). All three groups selected Online as their preferred instructional design modality (see Table 4).

Table 3

Ranked Level of Preference in Modalities for Teaching

Participant Group	Modality	<i>M</i>	<i>SD</i>
Instructors	Onsite	1.95	1.053
	Online	2.15	1.062
	Hybrid	2.46	0.862
	HyFlex	3.44	0.852
Instructional designers	Online	1.62	0.956
	Hybrid	2.25	0.830
	Onsite	2.74	1.066
	HyFlex	3.39	0.790

Professional development administrators	Online	1.82	1.023
	Onsite	2.31	1.080
	Hybrid	2.36	0.873
	HyFlex	3.51	0.756

Table 4

Rank Level of Preference in Modalities for Instructional Design

Participant Group	Modality	<i>M</i>	<i>SD</i>
Instructors	Online	1.91	0.952
	Onsite	1.96	1.020
	Hybrid	2.58	0.853
	HyFlex	3.55	0.782
Instructional designers	Online	1.32	0.610
	Hybrid	2.30	0.822
	Onsite	3.08	0.940
	HyFlex	3.30	0.822
Professional development administrators	Online	1.56	0.923
	Hybrid	2.39	0.891
	Onsite	2.59	1.095
	HyFlex	3.46	0.636

Results

The results of the study are presented in response to the four research questions.

Awareness of Neuromyths, General Knowledge about the Brain, Knowledge about the Brain and Learning, and Evidence-Based Practices among Professional Roles

Tables 5-8 present the results of the cross-tabulation analysis reporting on the percentage of accurate responses related to neuromyths, general knowledge about the brain, knowledge about the brain and learning, and evidence-based practices, broken down by participants' role. The tables also provide the answer key for each statement. For example, as shown in Table 5, lower percentages for accurate responses for the incorrect statement "A common sign of dyslexia is seeing letters backwards" were found among all three groups, including instructors (22%), instructional designers (7%), and administrators (28%). Similarly, lower percentages for accurate responses for the incorrect statement "Listening to classical music increases reasoning ability" were found among instructors (23%), instructional designers (21%), and administrators (24%). There were two statements in which there were greater differences in accurate responses by group. Instructional designers were found to have higher levels of awareness of the following two incorrect statements: "Individuals learn better when they receive information in their preferred learning styles (e.g., auditory, visual, kinesthetic)" (instructors, 38%; instructional designers, 64%; administrators, 46%), and "Some individuals are 'left-brained' and some are 'right-brained,' and this helps explain differences in learning" (instructors, 45%; instructional designers, 69%; administrators, 61%). Higher percentages for accurate responses were found across all groups for the incorrect statement "Learning problems associated with developmental differences in

brain function cannot be improved by education” (instructors, 84%; instructional designers, 81%; and administrators 85%).

Table 5

Percentage of Accurate Responses for Statements about Neuromyths by Role

Statement	Instructors (full-time, part-time)	Instructional Designers	Administrator (PD)	Answer Key
	%	%	%	
Listening to classical music increases reasoning ability	23	21	24	Incorrect
A common sign of dyslexia is seeing letters backwards	22	7	28	Incorrect
Individuals learn better when they receive information in their preferred learning styles (e.g., auditory, visual, kinesthetic)	38	64	46	Incorrect
Some individuals are “left-brained” and some are “right-brained,” and this helps explain differences in learning	45	69	61	Incorrect
Humans use only 10% of their brain	62	66	69	Incorrect
It is best for children to learn their native language before a second language is learned	66	70	70	Incorrect
There are critical periods in human development after which certain skills can no longer be learned	74	77	83	Incorrect
Learning problems associated with developmental differences in brain function cannot be improved by education	84	81	85	Incorrect

Table 6 shows a high percentage of accurate responses for several statements within general knowledge about the brain among all three groups. For example, 95% of instructors, 99% of instructional designers, and 94% of administrators provided accurate responses for the incorrect statement “The brain shuts down during sleep.” Similarly, 93% of instructors, 96% of instructional designers, and 94% of administrators provided accurate responses for the correct statement “Production of new neuronal connections in the brain continues over the lifespan.” By contrast, lower percentages of accurate responses were observed for the incorrect statement “The brain is a muscle,” with 52% of instructors, 45% of instructional designers, and 57% of administrators providing accurate responses.

Table 6

Percentage of Accurate Responses for Statements about General Knowledge about the Brain by Role

Statement	Instructors (full-time, part-time)	Instructional Designers	Administrators (PD)	Answer Key
	%	%	%	
The brain is a muscle	52	45	57	Incorrect
Normal brain development involves the birth and death of brain cells	69	72	74	Correct
Human brains are relatively as unique as fingerprints	73	77	89	Correct
When a brain region is damaged, other parts of the brain can sometimes take up its function	85	85	83	Correct
The left and right hemispheres of the brain work together	89	89	94	Correct
Neuroplasticity is the brain's ability to reorganize and rewire itself over the lifespan	91	90	85	Correct
Individuals use their brains 24 hours a day	93	98	91	Correct
Production of new neuronal connections in the brain continues over the lifespan	93	96	94	Correct
Chronic stress can change brain structure	93	92	96	Correct
Brain development has finished by the time children reach puberty	93	93	94	Incorrect
The brain shuts down during sleep	95	99	94	Incorrect

As to knowledge about the brain and learning, Table 7 shows a high percentage of accurate responses for several statements. For example, for the correct statement “Learning physically changes the brain,” 94% of instructors, 91% of instructional designers, and 82% of administrators provided accurate responses. Similarly, for the incorrect statement “Intelligence is fixed at birth,” 92% of instructors, 96% of instructional designers, and 94% of administrators provided accurate responses. By contrast, lower percentages of accurate responses were reported for the incorrect statement “Learning is due to the addition of new cells to the brain” by instructors (49%), instructional designers (63%), and administrators (46%).

Table 7

Percentage of Accurate Responses for Statements about Knowledge about the Brain and Learning by Role

Statement	Instructors (full-time, part-time)	Instructional Designers	Administrators (PD)	Answer Key
	%	%	%	
Learning is due to the addition of new cells to the brain	49	63	46	Incorrect
The brain acts as a filter to help individuals focus their attention	67	58	76	Correct
Individual learners show preferences for the mode in which they receive information (e.g., auditory, visual, kinesthetic)	79	78	83	Correct
Information is stored in networks of cells distributed throughout the brain	82	79	82	Correct
Extended practice of some mental processes can change the shape and structure of some parts of the brain	84	81	82	Correct
Learning occurs when there are changes to the connections between brain cells	88	77	78	Correct
Intelligence is fixed at birth	92	96	94	Incorrect
Learning physically changes the brain	94	91	82	Correct

As shown in Table 8, participants demonstrated high levels of knowledge of various evidence-based practices. For example, 97% of instructors, 98% of instructional designers, and 100% of administrators provided accurate responses for the correct statement “Emotions can affect human cognitive processes, including attention, learning and memory, reasoning, and problem-solving.” Similarly, 98% of all three groups provided accurate responses for the correct statement “Meaningful feedback accelerates learning” while 97% of instructors, 99% of instructional designers, and 98% of administrators provided accurate responses for the correct statement “Sleep has a vital role in memory.” By contrast, lower percentages of accurate responses were recorded for the incorrect statement “Differentiated instruction is individualized instruction” and the correct statement “Critical thinking requires epistemic cognition.” Specifically, only 38% of instructors, 50% of instructional designers, and 52% of administrators provided accurate responses for the incorrect statement about differentiated instruction. Similarly, only 36% of instructors, 39% of instructional designers, and 44% of administrators provided accurate responses for the correct statement about critical thinking.

Table 8*Percentage of Accurate Responses for Statements About Evidenced-Based Practices by Role*

Statement	Instructors (full-time, part-time)	Instructional Designers	Administrator (PD)	Answer Key
	%	%	%	
Differentiated instruction is individualized instruction	38	50	52	Incorrect
Critical thinking requires epistemic cognition	36	39	44	Correct
Focused attention is essential for learning new information	63	62	43	Correct
Testing, in general, tends to detract from learning	68	59	54	Incorrect
Experts and novices approach solving problems in essentially the same way	73	84	78	Incorrect
The human brain seeks and often quickly detects novelty	74	80	78	Correct
Rereading course materials is the best strategy for learning	75	83	78	Incorrect
Human memory works much like a digital recording device or video camera in that it accurately records the events individuals have experienced	78	84	72	Incorrect
Multitasking increases productivity	78	86	82	Incorrect
With respect to memory, massed instruction is superior to spaced instruction	80	92	83	Incorrect
Universal Design for Learning is a framework to improve and optimize teaching and learning for all people based on scientific insights into how humans learn	81	93	89	Correct
Frequent, low stakes assessments do not enhance learning	84	96	87	Incorrect
One is either born creative or not; creativity cannot be taught	86	94	96	Incorrect
Spaced studying of information is remembered better than massed studying of the same information	88	92	78	Correct
Metacognition plays a role in learning	94	97	96	Correct
Explaining the purpose of a learning activity helps engage students in that activity	94	99	98	Correct

The mind connects new information to prior knowledge	97	98	91	Correct
Repeated practice and rehearsal of learned material or a skill helps to consolidate it in long-term memory	97	95	96	Correct
Sleep has a vital role in memory consolidation	97	99	98	Correct
Emotions can affect human cognitive processes, including attention, learning and memory, reasoning, and problem-solving	97	98	100	Correct
Maintaining a positive environment in the classroom helps to promote learning	98	95	93	Correct
Stress can impair the ability of the brain to encode and recall memories	98	96	96	Correct
Meaningful feedback accelerates learning	98	98	98	Correct

Mean Percentage of Accurate Responses: Neuromyths, Knowledge About the Brain, and Knowledge About the Brain and Learning

A total of 27 statements examined neuromyths, general knowledge about the brain, and knowledge about the brain and learning. Inferential statistics, including ANOVA and post-hoc analysis, were used to compare the mean percentage of accurate responses. The data revealed that professional development administrators ($M = 76$) had a higher mean percentage of accurate responses on neuromyths, general information about the brain, and the knowledge of the brain and learning than instructional designers ($M = 75$) and instructors ($M = 73$; see Figure 1); however, the analysis of variance did not indicate any statistically significant differences between groups ($F = .867, p = .421$). There were also no statistically significant differences indicated between groups and institution type (public, private, for-profit) or institution level (two-year, four-year, other), and the percentage of accurate responses on neuromyths, general knowledge about the brain, and knowledge of the brain and learning. Additional analyses revealed no statistically significant differences between groups and demographic categories (full-time and part-time employment, highest degree earned, time from highest degree earned, age, and gender), and the percentage of accurate responses on neuromyths, general knowledge about the brain, and knowledge of the brain and learning.

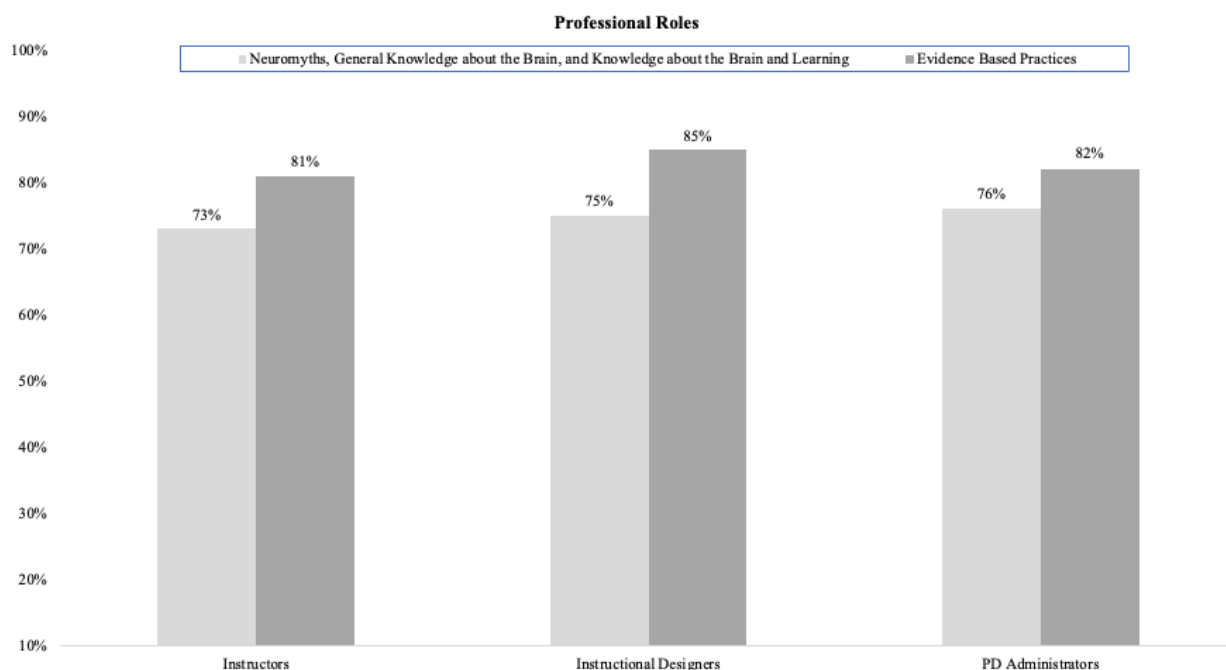
Mean Percentage of Accurate Responses: Evidence-Based Practices

A total of 23 statements were brought together to examine evidence-based practices. Inferential statistics including ANOVA and post-hoc analysis were used to compare the mean percentage of accurate responses. The analysis of variance indicated a statistically significant difference between groups ($F = 4.642, p = .010$) and the percentage of accurate responses on evidence-based practices. Instructional designers ($M = 85$) had a higher mean percentage of accurate responses on evidence-based practices than administrators ($M = 82$) and instructors ($M = 81$; see Figure 1). Post-hoc analysis using the Bonferroni method indicated a statistically significant difference between instructional designers and instructors ($p = .011$) while there were no statistically significant differences between instructional designers and administrators or between instructors and administrators. There were no statistically

significant differences found between groups and institution type (public, private, for-profit) or institution level (two-year, four-year, other) in awareness of evidence-based practices. Additional analyses revealed no statistically significant differences between groups and demographic categories (full-time and part-time employment, highest degree earned, time from highest degree earned, age, and gender) in the mean percentage of accurate responses on evidence-based practices.

Figure 1

Professional Role: Mean Percentage of Accurate Responses for Neuromyths, General Knowledge About the Brain, and Knowledge of the Brain and Learning, and Evidence-Based Practices Statements



Reading Journals and Mean Percentage of Accurate Responses

Participants who read journals related to neuroscience, psychology, learning sciences, and Mind, Brain, and Education (MBE) Science had a higher mean percentage of accurate responses on neuromyths, general knowledge about the brain, and knowledge about the brain and learning than participants who did not read or who planned to read these types of journals. An analysis of variance indicated statistically significant differences between groups who read, did not read, and planned to read journals related to neuroscience ($F = 8.898, p = .001$), psychology ($F = 7.200, p = .001$), learning sciences ($F = 9.931, p = .001$) and MBE Science ($F = 14.312, p = .001$). Post-hoc analysis using the Bonferroni method indicated a statistically significant difference between participants who read and participants who did not read and between participants who read and planned to read journals focused on neuroscience, psychology, learning sciences, and MBE Science. No significant difference was indicated between participants who did not read and participants who planned to read journals focused on neuroscience, psychology, learning sciences, and MBE science (see Table 9).

Table 9

Post-Hoc Analysis: Journals Related to Neuroscience, Psychology, Learning Sciences, and Mind, Brain and Education Science

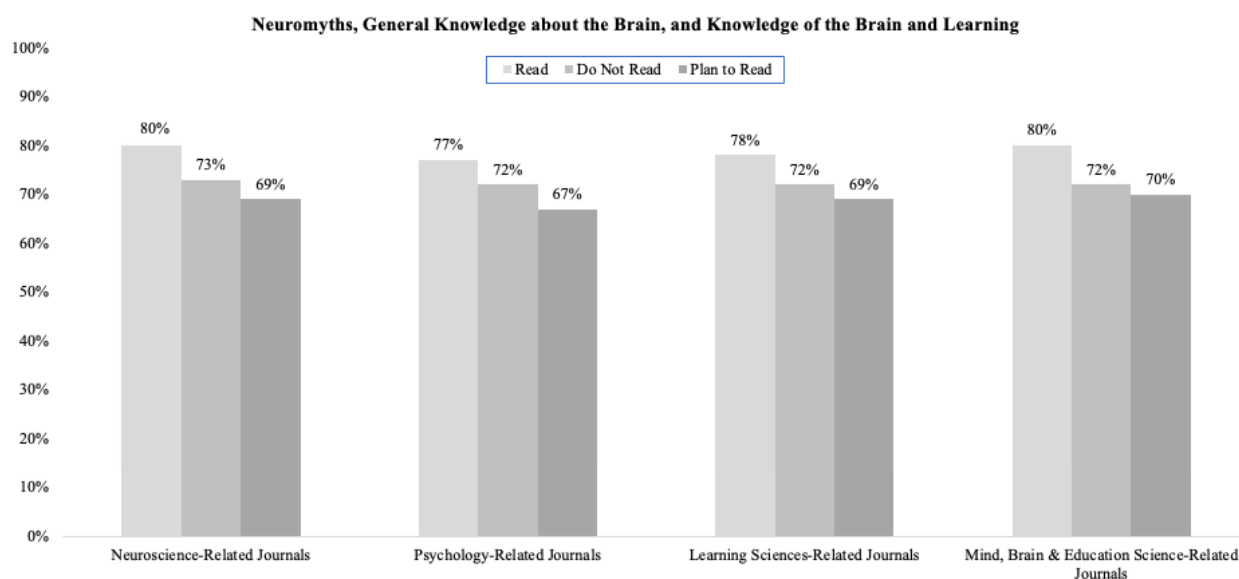
	Neuroscience Journals	Psychology Journals	Learning Sciences Journals	MBE Science Journals
Read vs. Do Not Read	$p = .001$	$p = .007$	$p = .004$	$p = .001$
Read vs. Plan to Read	$p = .001$	$p = .005$	$p = .001$	$p = .001$
Do Not Read vs. Plan to Read	$p = .581$	$p = .561$	$p = .567$	$p = .910$

Note: $p < .05$

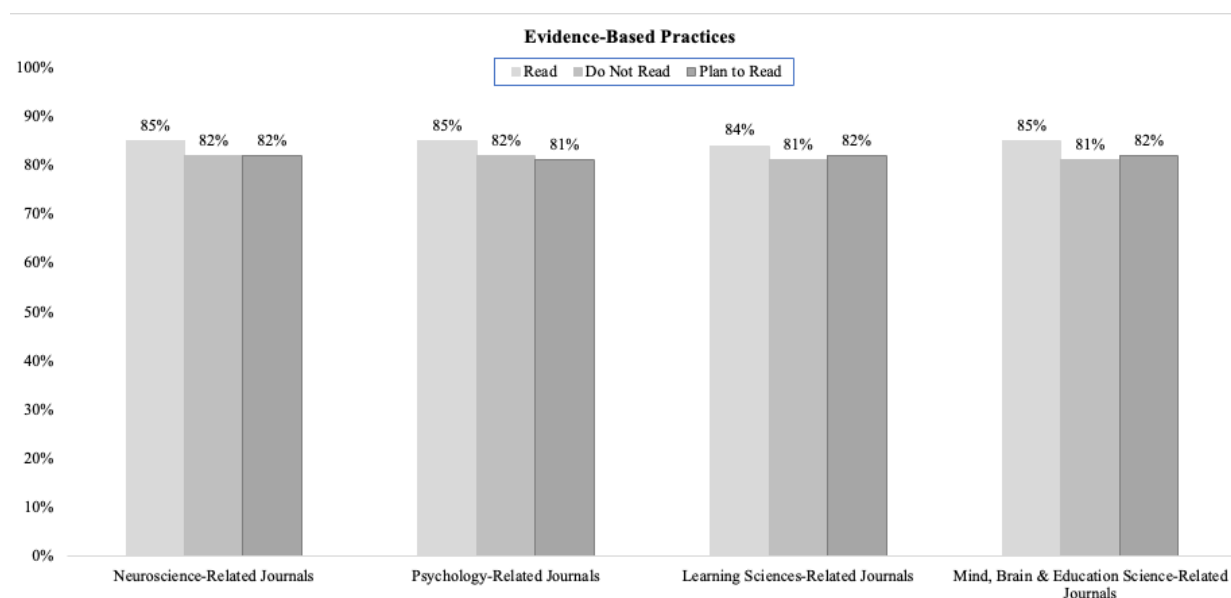
Participants who read journals related to neuroscience, psychology, learning sciences, and MBE Science had a higher mean percentage of accurate responses on evidence-based practices than participants who did not read or planned to read these types of journals (see Figure 3). An analysis of variance indicated statistically significant differences between groups with participants who read, who did not read, and who planned to read journals related to psychology ($F = 3.312, p = 0.038$) and MBE Science ($F = 3.927, p = 0.021$), and awareness of evidence-based practices. There were no statistically significant differences indicated between groups who read, did not read, or planned to read journals related to neuroscience ($F = 1.294, p = 0.276$) or the learning sciences ($F = 2.630, p = 0.074$) and awareness of evidence-based practices. Post-hoc analysis using the Bonferroni method indicated no statistically significant difference between participants who read and participants who did not read ($p = 0.051$), between participants who read and planned to read ($p = 0.247$), and between participants who do not read and plan to read ($p = 1.000$) journals focused on psychology. A statistically significant difference was indicated between participants who read and who did not read ($p = 0.019$) journals focused on MBE science. No statistically significant difference was found between participants who read and planned to read and between participants who did not read and planned to read journals focused on MBE science.

Figure 2

Reading Journals: Mean Percentage of Accurate Responses for Neuromyth, General Knowledge about the Brain, Knowledge of the Brain, and Learning Statements

**Figure 3**

Reading Journals: Mean Percentage of Accurate Responses for Evidence-based Practice Statements



Strategies, Principles, and Practices to Support Learning

Table 10 presents the results of the descriptive statistical analysis reporting on the percentage of responses related to participants' use of, and familiarity with, various strategies, principles, and practices to support learning. Participants were asked to identify out of a list of 29 strategies, principles, or practices that they were currently using, had used in the past, were

familiar with but had not yet used, and were unfamiliar with. The five strategies, principles, and practices used most by participants included Active Learning (82%), Scaffolding (77%), Low Stakes Assessment (75%), Backward Design (66%), and Project Based Learning (65%). It should be noted that approximately one-third of participants indicated they were teaching to students' learning styles (32%) and approximately one-third indicated they used to teach to students' learning styles (32%). The data also indicated that 12% of participants were teaching to right- and left-brain characteristics to support learning.

Table 10

Use of Strategies, Principles, and Practices to Support Learning

	Currently use	Have used in the past	Familiar with but not yet used	Unfamiliar with this
	%	%	%	%
Active learning	82	11	4	3
Scaffolding	77	13	3	7
Low stakes assessment	75	13	5	7
Backward design	66	12	10	12
Project-based learning	65	17	14	4
Metacognition	65	10	15	10
Universal design for learning	64	12	12	12
Experiential learning	62	17	17	4
Promoting growth mindset	60	10	18	12
Coaching	57	15	18	10
Elaboration	55	11	5	29
Spaced practice	52	16	14	18
Culturally responsive teaching	52	10	24	14
Cognitive load theory	53	9	13	25
Retrieval practice	51	19	9	21
High stakes assessment	49	34	10	7
Differentiated instruction	45	21	17	17
Mindfulness	43	10	35	12

Social-emotional learning	41	11	25	23
Multisensory learning	39	20	22	19
Creativity and innovation integration	37	11	14	38
Articulation	36	8	11	45
Interleaved practice	23	11	13	53
Task interspersal	23	5	14	58
Arts integration	21	15	26	38
Massed practice	19	23	21	37
Epistemic cognition	18	5	12	65
Teaching to students' learning styles	32	32	32	4
Teaching to right-brain and left-brain characteristics	13	11	50	26

Participants were asked to identify when and all of the ways in which they had learned about the 29 different strategies, principles, and practices, ranging from high school to graduate education and professional development to the Internet. Tables 11 and 12 report on the percentage of responses related to the ways in which participants had learned about the different strategies, principles, and practices. The data indicate that over one-third of participants learned about many evidence-based practices during their graduate education and during professional development prior to the pandemic, such as active learning, backward design, project-based learning, experiential learning, and low-stakes assessments, among others. It should also be noted that neuromyths such as teaching to learning styles or to right/left brain characteristics were identified as having higher percentages of participants having learned about them during graduate education and professional development during the pandemic, as well as through the Internet.

Table 11*Ways in Which Participants Learned About Strategies, Principles, and Practices*

	During my high school education	During my undergraduate education	During my graduate education	Colleagues	Online / Internet (e.g., content, blogs, podcasts, etc.)	Books	Articles
	%	%	%	%	%	%	%
Active Learning	8	17	44	30	32	25	32
Articulation	2	7	20	9	7	6	8
Arts Integration	4	11	18	11	12	7	10
Backward Design	2	7	34	29	30	25	26
Coaching	7	14	31	25	23	15	21
Cognitive Load Theory	2	6	31	18	20	16	21
Creativity & Innovation	4	8	24	15	14	10	13
Integration Culturally Responsive Teaching	1	7	25	30	34	21	28
Differentiated Instruction	5	15	32	23	27	22	26
Elaboration	8	19	29	12	15	14	14
Epistemic Cognition	2	5	13	5	7	5	7
Experiential Learning	5	17	39	30	24	15	24
High Stakes Assessment	19	24	38	19	17	17	17
Interleaved Practice	2	7	14	8	15	14	11
	During my high school education	During my under-graduate education	During my graduate education	Colleagues	Online / Internet (e.g., content, blogs, podcasts, etc.)	Books	Articles
	%	%	%	%	%	%	%
Low Stakes Assessment	8	18	39	26	27	23	25
Massed Practice	16	20	18	8	9	10	8
Metacognition	4	14	36	24	29	20	26
Mindfulness	1	7	19	24	24	15	20
Multisensory Learning	3	12	29	11	17	11	15
Project Based Learning	5	14	40	28	26	16	26
Promoting Growth Mindset	3	7	29	29	31	22	26

Retrieval Practice	21	24	30	15	22	23	21
Scaffolding	5	16	45	29	28	22	29
Social Emotional Learning	3	9	29	17	19	12	17
Spaced Practice	7	15	26	12	22	19	16
Task Interspersal	2	4	17	7	9	5	7
Universal Design for Learning	2	5	28	32	35	25	31
Teaching to right-brain and left-brain characteristics	8	13	16	7	14	8	8
Teaching to students' learning styles	8	18	36	18	23	16	19

Table 12

Additional Ways in Which Participants Learned About Strategies, Principles, and Practices

	PD prior to Pandemic	PD during the Pandemic	OLC Workshops	Unsure	N/A
	%	%	%	%	%
Active Learning	45	24	11	2	1
Articulation	15	8	3	8	12
Arts Integration	11	5	2	9	12
Backward Design	40	19	8	3	2
Coaching	31	16	4	7	4
Cognitive Load Theory	23	13	6	6	6
Creativity & Innovation	19	9	4	6	10
Integration Culturally Responsive Teaching	32	30	12	4	3
Differentiated Instruction	34	16	9	7	6
Elaboration	19	9	7	8	10
Epistemic Cognition	7	5	1	8	18
Experiential Learning	38	17	8	3	2
High Stakes Assessment	29	10	5	6	2
Interleaved Practice	16	9	5	6	16

	PD prior to Pandemic	PD during the Pandemic	OLC Workshops	Unsure	N/A
	%	%	%	%	%
Low Stakes Assessment	38	19	9	3	1
Massed Practice	11	6	5	10	13
Metacognition	33	17	8	4	4
Mindfulness	28	19	5	4	6
Multisensory Learning	21	9	6	8	9
Project Based Learning	41	17	7	2	2
Promoting Growth Mindset	35	20	8	4	4
Retrieval Practice	32	12	8	8	7
Scaffolding	42	20	8	2	1
Social Emotional Learning	28	14	5	5	7
Spaced Practice	27	15	7	8	7
Task Interspersal	12	4	2	7	17
Universal Design for Learning	42	26	15	3	3
Teaching to right-brain and left-brain characteristics	11	4	3	7	13
Teaching to students' learning styles	31	10	6	4	5

Participants were also asked which of the 29 listed practices, strategies, and principles on the survey they would like to learn more about. The list below reports on the top ten most frequently mentioned practices, strategies, and principles. Approximately one-third of all participants indicated they wanted to learn more about epistemic cognition, while roughly one-quarter wanted to learn more about task interspersal, interleaved practice, articulation, and creativity and innovation integration. Around one fifth of the participants wanted to learn more about cognitive load theory, culturally responsive teaching, elaboration, Universal Design for Learning, and social emotional learning.

1. Epistemic Cognition (32.3%)
2. Task Interspersal (27.7%)
3. Interleaved Practice (26.1%)
4. Articulation (23.8%)
5. Creativity and Innovation Integration (23.1%)
6. Arts Integration (21.1%)
7. Cognitive Load Theory (19.8%)

8. Culturally Responsive Teaching (19.1%)
9. Elaboration (18.8%)
10. Universal Design for Learning (17.8%) and Social Emotional Learning (17.8%)

Interest in Scientific Knowledge About the Brain

The study revealed that the participants found high value in scientific knowledge about the brain and its influence on learning and were also highly interested in learning more (see Table 13). In particular, most participants strongly agreed and agreed that scientific knowledge about the brain is valuable for their teaching practice (94%), course development (96%), and professional development (94%). Furthermore, 95% of the participants strongly agreed or agreed they were interested in learning more about the scientific knowledge about the brain and its influence on learning.

Table 13

Percentage of Responses for Statements About Value of and Interest in Scientific Knowledge About the Brain

	Valid Percent Strongly Disagree/ Disagree %	Valid Percent % Strongly Agree/Agree %	Not Applicable %
I find scientific knowledge about the brain and its influence on learning valuable for my teaching practice	3	94	3
I find scientific knowledge about the brain and its influence on learning valuable for course development	3	96	1
I find scientific knowledge about the brain and its influence on learning valuable for professional development	4	94	2
I am interested in learning more about the brain and its influence on learning	4	95	1

Limitations

This study has two key limitations. First, the study used convenience and snowball sampling. This may have led to a biased sample and underrepresentation since participants were invited based on accessibility and connections to the OLC and the research team. The second limitation is reduced response rates. When the survey was sent, higher education institutions across the United States shut for a second time due to the pandemic. Courses that had moved on campus quickly moved again to an online format. This shift may have impacted participant availability to complete the survey.

Discussion

The findings revealed that misconceptions such as dyslexia being associated with seeing letters backwards and the belief that classical music enhances reasoning ability remain prevalent across instructors, instructional designers, and administrators, with no statistically significant differences between role groups. These results confirm prior studies showing that deeply ingrained neuromyths continue to persist despite widespread educational efforts to debunk them (Newton, 2020; Tardif et al., 2015). The persistence of such beliefs is problematic because they can lead to misinformed instructional practices and may reinforce misconceptions about students with learning differences (Dekker et al., 2012). Notably, instructional designers showed comparatively higher degrees of awareness of two particularly pernicious neuromyths (Macdonald et al., 2017): teaching to learning styles and left/right-brain differences. Over half of full-time and part-time instructors indicated belief in those two neuromyths, and most professional development administrators believed the learning styles myth. These results point to a considerable knowledge gap, the presence of which further supports the need for targeted professional development that strengthens neuromyth awareness across all educator groups.

It should be noted that many of the findings related to neuromyths were similar to the findings from studies conducted with K-12 teachers nationally and internationally. While participants in this study worked in higher education, there were similar misconceptions regarding dyslexia as seeing letters backwards, music enhancing reasoning ability, individuals learning better when they receive information in their preferred learning style, or differences in learning being associated with being left-brained and right-brained (Bei et al., 2023; Tsang, 2024; Dekker et al., 2012; Ruiz-Martin et al., 2022; Simmers & Davidesco, 2024; Tunga & Çağıltay, 2023; van Dijk & Lane, 2018). The prevalence of these misconceptions within K-12 education and higher education reveals an opportunity to address persistent myths through professional development grounded in the learning sciences.

Encouragingly, high levels of accurate responses were observed for general brain knowledge and evidence-based practices, including the recognition that learning physically changes the brain, neuroplasticity continues across the lifespan, and emotions and feedback strongly influence learning outcomes. These findings align with a growing body of literature highlighting that educators are increasingly aware of neuroscience-informed principles that support effective pedagogy, such as the benefits of spaced practice, metacognition, and formative feedback (Corral & Carpenter, 2025; Dunlosky et al., 2013; Fleur et al., 2021; Wisniewski et al. 2020). However, the relatively low awareness of statements such as critical thinking requires epistemic cognition (correct) and differentiated instruction is individualized instruction (incorrect) reveals important gaps between general awareness and deep knowledge of evidence-based strategies. While educators may be familiar with broad cognitive and affective principles, they may struggle with translating these into complex instructional frameworks. Increasing awareness of critical thinking and epistemic cognition (Lunn Brownlee et al. 2022; Tarchi et al., 2025; Tamayo Alzate, 2025), as well as differentiated instruction (Liou et al., 2023; Pozas et al., 2021) can support pedagogical practice. Furthermore, translating the learning sciences into practice (Norman & Lotrecchiano, 2021) and neuroscience findings to classroom practices (Justus et al., 2024) can increase educator knowledge regarding research-informed practices.

The results indicated no statistically significant differences across professional roles, institution type, or demographic variables in accurate responses to neuromyths, general

knowledge about the brain, or knowledge about the brain and learning. This suggests that misconceptions about the brain and learning are not confined to particular professional or institutional groups. Prior research similarly shows that neuromyths persist across diverse educator populations, including teachers, instructional leaders, and faculty in higher education (Dekker et al., 2012; Newton, 2020). The finding that professional development administrators had slightly higher mean scores for accurate responses, though not statistically significant, may reflect their greater exposure to professional learning contexts. These patterns highlight the challenge of dispelling neuromyths through traditional pathways of professional development and emphasize the need to seek innovative approaches to embed neuroscience literacy explicitly into professional development programs (Dubinsky et al., 2013; Jolles & Jolles, 2021; Simmers & Davidesco, 2024) and professional learning communities (Justus et al., 2024).

In contrast, significant differences emerged in participants' knowledge of evidence-based practices, with instructional designers scoring higher than instructors. This finding aligns with Stefaniak and colleagues (2025), who report that instructional designers are often expected to incorporate evidence-based principles, pedagogical theory, and design research in their practice. Instructional designers, often trained in pedagogy and learning design, may have greater opportunities to engage with educational theory and research than instructors whose training may be more discipline specific (Wynants & Dennis, 2018). Given that effective teaching requires a solid grasp of how learning occurs, these findings call for intentional cross-role collaboration and the creation of shared learning experiences in professional development settings. As Newcombe (2023) emphasized, faculty must make detailed decisions about how they implement instructional and study strategies. Thus, professional development should be dynamic, data-informed, and inclusive of emerging practices such as spaced practice, retrieval-based learning, and cognitive load theory (Carpenter et al., 2022; Feenstra et al., 2024). Embedding these practices institutionally can build a more cohesive and scientifically grounded educational culture across all modalities of teaching and learning.

Another interesting finding is that participants who reported regularly reading journals in neuroscience, psychology, learning sciences, and MBE science consistently demonstrated higher accuracy in identifying both correct knowledge and evidence-based practices. This supports research showing that engagement with scholarly literature fosters critical evaluation skills and decreases susceptibility to neuromyths (Dekker et al., 2012; Rousseau, 2021; Seccia & Allee, 2024). These findings reinforce calls for professional development that integrates current scientific literature and provides structured opportunities for educators to critically appraise research claims. As noted by Lovett et al. (2023), cultivating a culture of data-informed teaching through access to scholarly resources can close the gap between research and practice.

The findings indicate that participants reported high levels of use of evidence-based instructional practices such as active learning (82%), scaffolding (77%), low-stakes assessment (75%), backward design (66%), project-based learning (65%), and metacognition (65%). These results are consistent with the broader literature emphasizing that these strategies enhance student engagement, promote deeper learning, and support knowledge transfer (Freeman et al., 2014; Park & Xu, 2024). The prevalent use of these practices by participants in this study could indicate that educators are increasingly adopting approaches grounded in the learning sciences, aligning with calls to move beyond traditional, lecture-centric teaching toward active, student-centered pedagogy. The prominence of backward

design and project-based learning also highlights a possible shift toward intentional course alignment and authentic, inquiry-based learning experiences, both of which are strongly supported in higher education contexts (Thomas, 2020). That said, recent research has found that didactic methods remain the predominant pedagogical choice for instructors in undergraduate STEM classrooms (Jackson et al., 2022), even when barriers like high course enrollment, inflexible learning spaces, and introductory-level courses were reduced or removed (Stains et al., 2018). Stains and his 30 co-authors called for institutions to overhaul tenure and promotion policies that instead incentivize, assess, and reward evidence-based instruction. Such a change would require increased investment in professional development programming to effectively train higher education's teaching force on evidence-based practices and neuromyth awareness in applicable contexts.

At the same time, the findings from this study reveal that a substantial proportion of participants continue to report using neuromyth-based practices. Approximately one-third of respondents indicated they currently teach to learning styles (32%), with another third reporting that they had used this approach in the past (32%), and 12% reported teaching to right- or left-brain characteristics. These findings echo previous research demonstrating the persistence of neuromyths among educators, even in the face of strong empirical evidence refuting their validity (Dekker et al., 2012; Newton, 2020). The continued use of learning styles is particularly concerning as it may take educators' time and resources away from implementing more effective, evidence-based strategies such as retrieval practice and spaced learning (Dunlosky et al., 2013). The fact that many participants reported first encountering neuromyths in graduate education, professional development during the pandemic, or online highlights how misinformation can circulate through both formal and informal learning channels, emphasizing the importance of critical engagement with scientific literature (Macdonald et al., 2017).

The significant interest expressed by participants in learning more about the brain and its influence on learning aligns with recent findings on the value of educational neuroscience in professional development. As Chang et al. (2021) and Hachem et al. (2022) note, educators who engage with neuroscience-informed professional learning report enhanced pedagogical insight and deeper understanding of student learning processes. In this study, nearly all participants agreed that brain-based knowledge is valuable for teaching, course development, and professional growth. This reinforces the potential of integrating translational research into ongoing faculty development initiatives. Moreover, the survey constructs examining knowledge about the brain, learning, and evidence-based practices are supported by studies such as Dubinsky et al. (2013) and Tan and Amiel (2019), which highlight the need for professional development that integrates neuroscience concepts for educators and connects them directly to classroom practice.

With growing demand for more flexible course delivery options (Coffey, 2023) and decreasing perceived value of college degrees (Kaplan, 2023; Lederman, 2023), course design and delivery have become critical in meeting the needs of students and preparing them for an increasingly competitive global workforce. Participants expressed a preference for online professional development, which can provide more accessible, flexible opportunities to engage with new research. Online professional development can be critical in providing faculty and instructional designers with new opportunities to learn about evidence-based practices based on scientific knowledge and transdisciplinary research from neuroscience, psychology, and education. Strengthening instructional quality by helping instructors ground their pedagogy in evidence-based practices can increase educational effectiveness.

Professional development must begin by addressing and dispelling persistent myths about how learning works, since misconceptions can undermine effective practice. Once these myths are replaced with accurate, research-based understandings that are grounded in psychology, neuroscience, and education, professional development can then introduce and reinforce evidence-based principles that guide effective teaching and learning strategies, thus providing a sustainable pathway to enhance instructional quality and, in turn, improve student outcomes in higher education.

As HEIs continue to traverse an increasingly dynamic and evolving educational landscape, it is imperative that administrators continually reassess their professional development strategy. Educators are encouraged to explore their disciplinary identities, contemplating what constitutes knowing in their disciplines; how this shapes curricular, pedagogic, and assessment choices; and what implications these questions have on teaching and learning. For example, we can explicate the chain of reactions when a university writing instructor comprehends the ramifications of the learning styles myth for the first time at a professional development workshop. They will quickly evaluate which of their teaching practices may have been influenced by the (now-debunked) belief that instructors should customize teaching to a student's stated learning style. They will recall past conversations about learning styles with students, parents, and colleagues. Motivated to seek alternative approaches supported by research, the instructor will then discover the merits of differentiated instruction versus individualized instruction. This new knowledge might later be shared with colleagues in the Writing department, sparking spirited discussions that culminate in collaborative revisions to instruction at both the micro and macro levels. The department collects internal evaluation data to help assess the implementation and impact of those revised instructional practices, which strengthens the department's self-study report for reaccreditation and future pursuits for additional professional development funds. In this way, the professional development experience extends beyond the concept of training into a catalyst for transformative teaching and learning change that supports student and institutional success.

Recommendations

Based on this study, there are three recommendations to support teaching and learning in higher education. Each recommendation emphasizes the importance of aligning practice with research from the learning sciences to prepare graduates for an increasingly complex global workforce.

Ground Teaching in Evidence-Based Practices

The Hippocratic Oath in Medicine reminds physicians to protect patients and to do no harm. Similarly, educators should follow suit in their approach to instructional design and teaching, ensuring that educational practices are grounded in research rather than false assumptions. Evidence-based practices are needed to support the foundations of an individual's thinking abilities, and consequently, society's democratic foundations. Furthermore, evidence-based teaching will help to bridge the gap between scientific research and practice while helping educators justify their instructional approaches and continuously improve them in response to the changing needs of diverse students.

Stay Current

Professional development needs in higher education reflect global trends toward a demand for constant upskilling and reskilling to keep pace with continually advancing fields.

A broader range of students and a narrowing number of applicants have forced HEIs to rethink the skill sets required of those designing and providing teaching and learning experiences. Independent of the teaching-learning modality (e.g., online, hybrid, onsite, or HyFlex), better knowledge of how and why the brain learns needs to become common knowledge for professional educators. Explicit instruction, implicit reinforcement, and updating about neuromyths should be a part of both initial formation as well as continual professional development. Additionally, engaging with scientific literature is crucial for educators because it keeps their knowledge current and grounded in the latest research on teaching, learning, and human development. By actively reading peer-reviewed articles, educators can critically evaluate which instructional approaches are supported by evidence, identify emerging trends, and avoid relying on outdated or untested methods.

Continuous Professional Growth

The value of a higher education degree depends on its ability to prepare students for the future along with learning from the past. Educators with antiquated understandings or unsubstantiated beliefs about how the brain learns will quickly lose credibility with advancements in research, the ubiquity of artificial intelligence, and the accessibility of digital learning tools. Continuous professional growth requires intentional institutional support, including opportunities to engage in instructional training, learning communities, mentorship, and collaborative professional networks. By providing professional development opportunities that integrate the latest learning sciences research and encourage educators to engage in innovation, reflection, and refinement of practice, HEIs can foster a culture of continuous growth that strengthens teaching quality and sustains institutional relevance.

To remain relevant in the coming decades, HEIs must adapt by both learning from the past and embracing the latest research and technologies of today. Unlike K-12 education in which teachers receive extensive pre-service training, most professors enter higher education with little formal preparation, learning to teach by drawing on their own student experiences and trial-and-error teaching (Newcombe, 2023). Educators must ground teaching in evidence-based practices, stay current, and engage in continuous professional growth. Ultimately, HEIs need to empower educators with the time, resources, and professional development to prepare graduates to thrive in a dynamic, competitive, and ever-evolving global workforce.

Conclusions

The results of the study indicate high levels of awareness with evidence-based practices among all participants. The results also revealed opportunities to increase levels of awareness regarding neuromyths, general knowledge about the brain, and knowledge about the brain and learning. There are some areas of knowledge that continue to lag, especially with respect to learning styles and the idea of left-brained/right-brained learners. Notably, the research indicates a strong interest among instructors, instructional designers, and administrators in gaining scientific knowledge about the brain and its impact on learning. Moreover, all three groups recognize the value of such knowledge in teaching, course development, and professional growth.

As HEIs navigate the integration of AI into curricula, professional development will be critical as well to supporting strategies, principles, and practices that support learning. This study suggests that professional development serves as a unique platform for HEIs to disseminate current and emerging research through workshops, seminars, and certificate programs that bring together educators, instructional designers, and administrators.

Professional development and exposure to transdisciplinary research and resources can enhance awareness of neuromyths, general knowledge about the brain and learning, and evidence-based practices. Finally, this study contributes to understanding the importance of integrating research from neuroscience, psychology, and education into professional development offerings so faculty and instructional designers can utilize this scientific-based knowledge within their course development, teaching, and assessment across all course modalities to support student and institutional success.

Declarations**Conflict of Interest**

The authors conducted the research under strict ethical standard. They declare no conflicts of interest and received no external funding.

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Development and Validation of a Questionnaire for Self-regulated Learning in Blended or Technology-mediated Learning Environments in Higher Education

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Abstract

Higher education has undergone significant transformations with the incorporation of blended learning. Self-regulated learning has been identified as a crucial factor for academic success in this context. However, the measurement of self-regulated learning in blended learning environments remains limited. This study aims to develop and validate a questionnaire to assess self-regulated learning in Chilean university students participating in blended learning environments. An instrumental study was conducted with a sample of 1,147 university students from an institution in southern Chile. A sequential methodological design was used to validate the dimensions of the questionnaire. The sample was randomly divided into two groups, 556 students for exploratory factor analyses and 591 students for confirmatory factor analyses. The final questionnaire comprises 71 items distributed in three main dimensions: Planning, Execution and Assessment, with specific sub-dimensions for each. The psychometric analysis revealed adequate validity and reliability indices, confirming the factorial structure of the questionnaire and its ability to measure self-regulated learning in blended learning contexts.

Keywords: Self-regulated learning; blended learning; higher education; psychometric validation

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Introduction

The experience of teaching and learning during emergency remote education (ERE) highlighted the importance of designing flexible and versatile learning spaces, allowing teachers and university authorities to reflect on integrating virtual tools with traditional face-to-face education (Gómez, 2020; Kuklinski & Cobo, 2020). The international trend is to develop practices for high-quality virtual teaching (Zhu & Liu, 2020), with blended learning (BL) emerging as a leading model (Cobo-Rendón et al., 2022; Gqibani, 2022; Kamali & Bagheri-Nesami, 2022; Lobos et al., 2023a). BL enables the delivery of content in a virtual modality while allowing face-to-face sessions for active learning (Murphy, 2020; Rasheed et al., 2020). Nevertheless, researchers (Chiu & Hinds, 2022; Kamali & Bagheri-Nesami, 2022; Lobos et al., 2023b; Lobos et al. 2023c) have reported that students face new challenges with BL, such as distraction, lack of direct social interaction, demand for greater autonomy, and better management of time and educational space. Self-regulated students would be better equipped to overcome these challenges since they could apply strategies to stay focused, seek help, and make timely adjustments in their studies. However, little is known about self-regulated learning (SRL) in BL contexts, since not only did learning environments change, but so did the strategies students use to self-regulate their learning. Therefore, SRL had evolved in form and content, rendering traditional instruments insufficient to capture its current expression. This study adopted an instrumental design, expecting to develop a questionnaire that measures SRL in BL university educational contexts.

Literature Review

Blended Learning in Higher Education

BL is an educational modality that combines face-to-face and virtual education. Unlike traditional face-to-face learning, which doesn't involve online academic activities, and virtual learning, which doesn't include face-to-face academic activities, BL combines both with the aim of leveraging the advantages of the strategies, technologies, and pedagogical activities of both modalities for the benefit of student learning (Bartolomé Pina, 2004; Hrastinski, 2019). Thus, BL is considered an effective teaching method since it provides flexible, timely, and continuous learning (Brown, 2016). BL's virtual component consists of virtual classrooms, enabling asynchronous learning through diverse innovative resources (Martínez & Jiménez, 2020), and emphasizes student independence, critical thinking, and collaborative work through meaningful activities (Martínez & Jiménez, 2020; Prasad et al., 2013). BL has been proven to be as effective as, or more effective than, traditional face-to-face teaching (Besser et al., 2022; Broadbent, 2017; Vuttanon et al., 2021).

The most relevant benefits of BL in higher education are: (a) increased accessibility for students who would otherwise struggle to attend a traditional university due to geographical or mobility barriers (Ibrahim Qetesh et al., 2020; Megahed & Ghoneim, 2022); (b) integrating both face-to-face and online teaching methods, providing a richer educational experience (Vuttanon et al., 2021); (c) online learning platforms can offer adaptive materials, allowing students to progress at their own pace (Broadbent, 2017; Guppy et al., 2022); (d) digital tools facilitate collaboration and communication between students and teachers beyond physical limitations (Pollock, 2022); (e) face-to-face sessions can focus on activities that benefit from direct interaction, such as debates, labs, and group work, while lectures and theoretical content can be

covered online (Cobo-Rendón et al., 2022); and (f) maintaining an online learning infrastructure ensures that students can continue their studies without significant interruptions, regardless of external circumstances (Besser et al., 2022). Also, the use of digital tools and platforms in BL higher education better prepares students for an increasingly digitized work environment, as it promotes skills such as self-management, digital communication, and autonomous problem-solving.

Currently, higher education is moving towards a BL model because it grants greater effectiveness and efficiency to educational processes and aligns with the needs and expectations of students and the demands of the contemporary world (Järvelä et al., 2021; Molenaar, 2022). In the context of Chilean higher education, Law No. 21,091 recognizes BL, understood as the combination of face-to-face and virtual classes, for undergraduate programs (Ministry of Education of Chile, 2018). Therefore, Chilean higher education institutions offer fully face-to-face modalities without online tools or activities; fully virtual modalities with asynchronous and/or synchronous online activities; a blended modality where some courses are taught entirely face-to-face and others entirely virtually; and a blended modality where classes are entirely face-to-face but are supplemented with asynchronous online activities and resources.

Self-Regulated Learning (SRL) and Higher Education

SRL is understood as an active process through which students direct, monitor, and reflect on their learning, adjusting their strategies according to personal goals and contextual demands (Zimmerman, 2000). This ability involves cognitive, motivational, emotional, and behavioral components that influence academic performance and autonomy (Ganda & Boruchovitch, 2018).

Three theoretical models have shaped the conceptualization of SRL: Zimmerman (1998) proposed a three-phase model (forethought, performance, and self-reflection); Winne and Hadwin (1998) described four stages (task definition, goal setting and planning, enactment, and adaptation); and Pintrich (2000) outlined a four-phase model (planning, monitoring, control, and reflection). While Zimmerman and Winne and Hadwin primarily focus on cognitive processes, Pintrich highlights the emotional aspects involved in learning regulation (Ganda & Boruchovitch, 2018; Trías & Huertas, 2020). Across all models, learners are seen as proactive agents who strategically engage with their learning goals while mediating between their individual characteristics and the learning environment.

Empirical evidence supports the value of SRL in higher education. Students who develop SRL tend to achieve higher academic outcomes, demonstrate greater engagement in learning tasks, and exhibit positive emotions toward academic experiences. Furthermore, they report stronger academic self-efficacy, which enhances their confidence in overcoming academic challenges (Alegre, 2014; Gómez Martínez & Romero Medina, 2019; Marcelo & Rijo, 2019; Xu et al., 2022). Research also indicates that SRL increases course completion rates, strengthens problem-solving and conflict resolution skills, promotes responsibility and independence, and facilitates adaptation to university life (Broadbent, 2017; Cerezo et al., 2020; Jin et al., 2023). Moreover, self-regulated students positively impact teaching by reducing the need for constant supervision, allowing instructors to engage in more meaningful pedagogical strategies (Cerezo et al., 2020; Lobos et al., 2023a). These students typically manage their time effectively, set clear

goals, use strategic learning methods, and demonstrate high levels of autonomy and motivation. In contrast, students with low SRL skills are at risk of academic failure, delayed graduation, and dropping out (Advíncula & Aguirre, 2021).

The hybrid nature of BL requires learners to exercise greater control over their schedules, maintain focus in the face of distractions, and regulate their engagement with academic tasks without continuous teacher presence. However, research reveals that many students face difficulties with SRL in virtual or hybrid environments, particularly in planning, time estimation, and managing distractions such as social media, challenges that are especially pronounced among disadvantaged student populations (Hodges et al., 2020; Varas-Meza et al., 2020; Viberg et al., 2018). Along the same lines, Barnard et al. (2009) pointed out that, due to the characteristics of online and blended learning such as high levels of autonomy and the lack of external structure, it is essential to have specific instruments that assess self-regulatory skills in these contexts.

Measuring SRL in BL

The measurement of SRL has evolved with diverse instruments shaped by new findings. Hernández Barrios and Camargo Uribe (2017) reviewed SRL measurement in Ibero-American higher education, identifying 12 instruments: 4 unidimensional, 3 addressing specific facets, and 1 focused on virtual education. León-Ron et al. (2020) reviewed SRL instruments across educational levels (2009–2019), finding 31. They noted the Motivated Strategies for Learning Questionnaire (MSLQ) as the most used and highlighted limited research in Central and South America. Likewise, Roth et al. (2016) conducted a systematic review of self-report instruments used in higher education, identifying a predominance of questionnaires based on quantitative offline standards and highlighting the lack of instruments that assess emotional and motivational regulation. They also noted a growing trend toward course- or domain-specific instruments rather than general ones, which is particularly relevant for BL contexts. Maldonado-Mahauad et al. (2020) identified SRL instruments (1991–2016) for MOOCs, finding most were created in the 1990s for face-to-face contexts. Virtual components in these instruments fail to address current technology's nuances. Instruments for virtual higher education include Learning and Study Strategies Inventory (LASSI), Online Strategies for Learning Questionnaire (OSLQ), and Self-regulated Online Learning Questionnaire (SOL-Q). LASSI and OSLQ were designed in the 1990s, while SOL-Q (Jansen et al., 2017) partially addresses SRL.

A review of Web of Science (WOS), Scopus (2018–2023) and SciELO found one relevant instrument: the Self-Regulation Questionnaire for Online Learning (SRL-O), by Broadbent et al. (2023), based on face-to-face SRL instruments. It focuses on the planning stage but lacks coverage of other SRL stages in Zimmerman's theory.

In summary, although existing instruments have contributed to the understanding of SRL, they present limitations in addressing BL environments' demands. The transformations experienced in education following the COVID-19 pandemic marked a turning point in the ways teaching and learning are carried out, altering the ways in which students regulate their own learning, making conventional instruments inadequate for capturing the present-day characteristics of SRL. Therefore, this study aims to develop an instrument for measuring SRL in BL university contexts. Unlike traditional questionnaires (e.g., MSLQ, LASSI, OSLQ), which were originally designed for face-to-face contexts or for those with partial technological

mediation, this instrument explicitly integrates the phases proposed by Zimmerman (2000) and the categories from Winne and Hadwin (1998), adapting them to the challenges of BL. The construction of items was not limited to replicating classical definitions but rather drew on a qualitative study with students in hybrid environments, which allows for the incorporation of emerging behaviors related to the use of digital resources, management of the virtual study environment, preparation of online materials, monitoring through external parameters (such as comparisons with peers and teacher feedback), and motivational reactions specific to sustaining effort without the physical structure. These dimensions, which are rarely considered in previous instruments, justified the need for a new questionnaire that more accurately captures SRL strategies in BL modalities.

Method

The instrumental study design (Ato et al., 2013) was employed to design and validate questionnaires or measurement scales, thus meeting the objective of evaluating the psychometric properties of the SRL questionnaire among Chilean university students in BL. To validate the dimensions of the questionnaire, a sequential methodological design was used, beginning with an in-depth qualitative phase to gather insights for the quantitative phase (Creswell & Creswell, 2023).

Participants

The responses of 1,147 students (596 women) from a university in southern Chile were examined, which corresponds to 4.3% of the 26,644 students invited to the study. The sample included students from first to fifth year, the vast majority (89.45%) being first-year students. The participants ranged from 17 to 37 years, with a mean age of 18.9 (SD = 2.2). The sample included students of the following areas of study: Administration and Commerce (7.0%), Agriculture and Marine Sciences (3.4%), Art and Architecture (4.3%), Natural Sciences and Mathematics (11.4%), Social and Behavioral Sciences (7.3%), Law (3.7%), Education (12.1%), Humanities (2.7%), Engineering and Technology (29.7%), and Health (18.4%). The selection of participants was carried out through a non-probabilistic convenience sampling. The participants' learning environment consisted of subjects with a BL modality, which consisted of face-to-face classes with complementary asynchronous online academic activities hosted on the university's CANVAS learning management system.

Instrument

Questionnaire for SRL in BL

The initial version of the instrument was designed with a 5-point Likert scale, where 1 is “never” and 5 is “always.” To construct the instrument, the authors relied on León-Ron et al. (2020)'s findings, and on a literature review carried out in the Wos, Scopus, and SciELO databases to search for articles published after 2019 that reported SRL instruments in virtual contexts. The SRL-O (Broadbent et al., 2023) was identified, which had items adapted from SRL instruments for face-to-face contexts for online education. Given that, a qualitative study was conducted to collect information on SRL from students who have experienced studying in a BL university context (Lobos et al., 2024), resulting in an instrument with 152 items divided into three dimensions: Planning (64), Execution (53), and Assessment (37). For each of these dimensions, the items were organized into subdimensions (Appendix 1).

Content validity was studied through expert judgment, selecting five professionals under three criteria: (a) Master's and/or Doctorate degree, considering that this level of education guarantees an advanced command of the theoretical and methodological frameworks, (b) scientific production linked to SRL, to ensure up-to-date and specialized knowledge, and (c) experience in e-learning or BL education, as the instrument was designed for these contexts, requiring validation sensitive to their pedagogical and technological aspects. The level of agreement among the experts, according to Aiken's V coefficient (Merino-Soto, 2018), was 0.92. As a result, the number of items was reduced from 152 to 84 (Table 1). This decrease is primarily explained by the presence of items that intentionally addressed the same content using different formulations. This strategy was adopted to evaluate the clarity and effectiveness of various wordings, allowing the judges to select the versions with clearer and more precise wording. Additionally, items that did not demonstrate high relevance or pertinence to their assigned dimension were discarded. Within the Planning dimension, the subdimensions *Preparation of virtual learning materials* and *Study environment preparation* were merged, based on the judges' assessment that virtual materials do not differ substantially from those used in in-person contexts.

Table 1

Distribution of SRL Questionnaire Items Following Expert Judgment Process

Dimensions	Sub-dimensions	Initial items	Final items	Elimination criteria
Planning (from 64 to 37)	Time planning	8	6	1 (C); 1 (R)
	Study environment preparation	8	5	2 (C); 3 (R); + 2
	Activity planning	7	5	2 (I)
	Preparation of technological devices	11	6	3 (C); 1 (I); 1(R)
	Preparation of virtual learning materials	8	0	3 (C), 3 (R); - 2
	Study strategy planning	7	5	2 (I)
	Goal setting	7	5	2 (R)
	Self-motivation	8	5	1 (C); 2 (R)
	Work approach monitoring	11	4	4 (C); 3 (R)
Execution (from 53 to 27)	Learning achievement monitoring	14	7	5 (C); 1 (I); 1 (R)
	Time and activity organization monitoring	15	8	5 (C); 2 (R)
	Help-seeking strategies	13	8	4 (C); 1 (I)
Assessment (from 37 to 20)	Self-judgment	14	10	4 (C)
	Self-reaction and self-satisfaction	23	10	5 (C); 5 (R); 3 (I)

Note. (C) indicates the items removed due to lack of clarity in wording and for being duplicated or redundant with better-phrased items; (R) corresponds to items discarded due to low relevance to the subdimension; (I) refers to items eliminated due to their low importance for the estimation of the subdimension.

Using this version, an initial EFA was conducted, with a sample of 202 university students,

separate from the main study sample of 1,147 participants, with the aim of improving and/or replacing items to ensure that the most relevant are included for the final application (Soriano Rodríguez, 2015).

Planning Dimension. The subdimensions *Time planning* and *Activity planning* were merged and renamed as *Time management*, including items 1, 2, 6, 12, and 13, plus a new item. *Study strategy planning*, *Goal setting* and *Self-motivation* were merged into a new subdimension: *Management of study goals and purposes*, which included items 23, 24, 25, 28, 30, 33, and 34. The subdimension *Study environment preparation* remained with items 7, 8, 18, and 19, plus a new item. The remaining items on the subdimension *Preparation of technological devices* appeared to focus more on resources rather than on preparing devices, changing the name to *Preparation of digital materials and resources*, including items 10, 20, and 26, plus a new item. The other items were removed due to having factor loadings below 0.4. Since some of these were of high theoretical relevance, the three new items were developed to be clearer in evaluating their intended constructs. In total, out of the original 37 items, 17 items were removed, and 3 new ones were created. Consequently, the Planning dimension comprised 4 subdimensions with 23 items.

Execution Dimension. The subdimensions *Work approach monitoring*, *Learning achievement monitoring* and *Time and activity organization monitoring* were merged into a new subdimension: *Personal strategies for learning monitoring*, including items 38, 39, 40, 46, 47, 49, 52, 53, 54, 56, 57, and 58. A new factor was formed with items 44 and 45. Since both addressed external comparison parameters used by students to evaluate their study, a new subdimension, *External parameters for learning monitoring*, was created and strengthened with four additional items addressing other external information sources available for study monitoring. The subdimension *Help-seeking strategies* remained with its original items, except for 57 and 58, which refer to the search for support materials, loading onto *Personal strategies for learning monitoring*. The remaining items alluded to strategies for seeking help from other educational actors, changing the name to *Social strategies for learning monitoring*. A new item was created to include the professor as a source of support. The other items were removed due to factor loadings below 0.4. In total, out of the original 27 items, 7 items were removed, and 5 new ones were created. Therefore, the Execution dimension consisted of 3 subdimensions with 25 items.

Assessment Dimension. The items were organized into four factors. Most items were grouped into three subdimensions regarding self-judgments: *Evaluation of the study environment and materials* (items 68, 69, 71, 72, and 79), *Evaluation of study strategies* (items 65, 66, 67, 74, 75, 76, and 77), and *Evaluation of the learning quality*. This last factor remained composed of two items with factor loadings below 0.4, and so they were eliminated. Given the relevance of having a subdimension where the student evaluates the quality of their learning, 5 new items were designed. In the fourth dimension, items 82, 83, and 84 were grouped due to being linked to cognitive-motivational themes that include affective elements involved in the processes of success or failure in learning. To strengthen the subdimension, three new items were designed. Therefore, its name changed from *Self-reaction and self-satisfaction* to *Self-motivation reactions*. The other items were removed due to factor loadings below 0.4. In total, from the original 20 items, 5 were removed and 8 new ones were created, leaving the Assessment dimension with a

total of 23 items.

The final version of the instrument was piloted with 32 university students to evaluate the clarity of the instructions and the appropriateness of the language, with no issues reported.

Procedure

Research Procedures

The final version of the questionnaire was transferred to an electronic form and was sent once via institutional email to the student population. The email detailed the purposes and boundaries of the study. Before answering the questions, participants were required to sign an informed consent form. The form remained open from January to March of 2024.

Data Analysis Procedures

For the statistical analyses, the sample was randomly divided into two groups, considering the faculty to which they belonged, the declared major and gender. Subsequently, a descriptive analysis of the sample was conducted. Also, a verification of outliers was performed using Mahalanobis distance, identifying outliers in 100 observations. The items, in univariate analysis, presented skewness and kurtosis within the range of ± 1.5 , adhering to the criteria suggested by Pérez and Medrano (2007), and therefore were not eliminated.

An EFA was conducted with the first subsample (556 students) employing a polychoric correlation matrix, given that the items were evaluated using a 5-point ordinal scale. The suitability of data was assessed using the Kaiser-Meyer-Olkin (KMO) sampling adequacy index and Bartlett's test of sphericity. The optimal number of factors was determined using Horn's parallel analysis and the Eigenvalue criterion. The EFA was performed using generalized least squares extraction and geomin oblique rotation. An iterative process was carried out to improve the factorial solution where in each iteration, potential issues such as cross-loadings or items without significant loadings were analyzed to decide on their elimination. This process was repeated for each dimension until a final solution was obtained without issues, where each item was associated with a single factor with a loading of 0.4 or higher.

Subsequently, a CFA was conducted with the second subsample (591 students). The correlation matrix of all considered items verified the absence of collinearity, as no values exceeded 0.85 (Cupani, 2012; Kline, 2011). Robust Maximum Likelihood (RML) estimation was employed. According to Holgado-Tello et al. (2016), this method is a variant of the Maximum Likelihood (ML) approach, designed to address the limitations that arise when data do not meet the assumptions of multivariate normality, and the variables are ordinal in nature. Unlike the traditional ML method, which assumes normality in observed variables, RML uses an asymptotic covariance (AC) matrix to generate a freely distributed weight matrix. This approach allows for a more precise fit when the observed variables do not follow a normal distribution (Holgado-Tello et al., 2016).

The CFA was conducted for each scale and its subdimensions. An analysis was performed based on a third-order factorial structure, considering the subdimensions of each scale, as well as how these scales are explained by a broader factor (SRL). For goodness-of-fit, the indices CFI and TLI (>0.90) and RMSEA and SRMR (<0.10) were considered (Hair et al., 2019). Reliability was

assessed using Cronbach's α and McDonald's ω coefficient, and variance extracted was evaluated using the AVE coefficient. These analyses were performed using JASP software (version 0.18.3.0).

Results

The results are organized based on the analyses conducted. First, a descriptive analysis of the sample is presented, followed by an EFA for each scale. Subsequently, a CFA was performed for each scale and the third-order structure. The reliability of the subdimensions, each scale, and the complete questionnaire were reported.

Descriptive Analysis

The descriptive analyses of the questionnaire's items can be seen in Appendix 2. Most items exhibit skewness and kurtosis within the range of ± 1.5 . No items were removed, indicating that the response distribution is concentrated on the higher scores of the scale. No anomalies were found.

EFA of the Scales Comprising SRL in BL Questionnaire

The factorial validity of each scale, as well as their subdimensions, was assessed.

EFA of the Planning Scale

The KMO index has a value of .91, and Bartlett's test of sphericity yielded a value of $X^2(210) = 65,481.75$, $p < .001$, indicating that the polychoric correlation matrix is suitable for conducting a factor analysis. Using Horn's parallel analysis, it was determined that the optimal number of factors for the factorial solution is four, while the Eigenvalue criterion suggested five factors. Given this variation, a solution considering five factors was initially evaluated (Table 2).

Table 2

Iterative Process for Improving the Factorial Solution of the Planning Scale

Solution No.	Items	Factors	Explained variance	Detected issues	Action
1	23	5	53.34	Items with cross-loadings: 10–12	Remove items 10–12
2	21	5	54.36	Item without loading: 5	Remove item 5
3	20	5	54.61	Items with cross-loadings: 18–19	Remove items 18–19
4	18	5	55.44	No issues	

Table 3 presents the final factorial solution with 18 items for the Planning scale. The first factor, *Time management*, comprises items PLA14, PLA15, PLA16, and PLA17. The second factor, *Study environment preparation*, comprises items PLA9, PLA11, and PLA13. The third factor, *Learning purposes*, comprises items PLA1, PLA2, PLA3, and PLA4. The fourth factor, *Preparation of materials and digital resources*, comprises items PLA20, PLA21, PLA22, and PLA23. The fifth factor, *Study strategy selection*, comprises items PLA6, PLA7, and PLA8.

Table 3
Exploratory Factor Solution of the Planning Scale

Items	Factors				
	Time management	Study environment preparation	Learning purposes	Preparation of materials and digital resources	Study strategy selection
PLA16	.84				
PLA15	.69				
PLA14	.59				
PLA17	.53				
PLA11		.83			
PLA9		.78			
PLA13		.70			
PLA2			.72		
PLA4			.67		
PLA3			.66		
PLA1			.66		
PLA20				.71	
PLA21				.68	
PLA22				.57	
PLA23				.54	
PLA7					.90
PLA6					.70
PLA8					.65

Note. The extraction method used was Unweighted Least Squares and the rotation method was Oblimin with Kaiser normalization. The rotation converged in 8 iterations.

EFA of the Execution Scale

A KMO index of .92 was identified, and Bartlett's test of sphericity yielded a value of $X^2(300) = 7486.65$, $p < .001$, indicating that the correlation matrix is suitable for conducting a factor analysis. Using Horn's parallel analysis, it was determined that the optimal number of

factors for the factorial solution is three. However, the Eigenvalue criterion suggests that the optimal solution consists of four factors, so the analysis was conducted with four factors (Table 4).

Table 4

Iterative Process for Improving the Factorial Solution of the Execution Scale

Solution No.	Items	Factors	Explained variance	Detected issues	Action
1	25	4	52.16	Items without loading: 7–8–19–25	Remove items 7–8–19–25
2	21	4	56.19	Items with cross-loadings: 1–3–6–14–18–23	Remove items 1–3–6–14–18–23
3	15	3	56.07	Item with cross-loading: 2	Remove item 2
4	14	3	57.33	No issues	

Table 5 presents the final factorial solution of the Execution scale, consisting of 14 items. The first factor, *External parameters for self-monitoring*, comprises items EX20, EX21, EX22, and EX24. The second factor, *Personal strategies for self-monitoring*, comprises items EX4, EX5, EX9, EX10, EX11, and EX12. The third factor, *Social strategies for self-monitoring*, comprises items EX13, EX15, EX16, and EX17.

Table 5

Factorial Solution of the Execution Scale

Items	Factors		
	External parameters for self-monitoring	Personal strategies for self-monitoring	Social strategies for self-monitoring
EX21	.91		
EX22	.79		
EX20	.76		
EX24	.70		
EX9		.76	
EX12		.68	
EX10		.68	
EX11		.65	

EX5	.61	
EX4	.46	
EX15		.93
EX16		.93
EX17		.77
EX13		.51

Note. Method of extraction: Unweighted least squares. Method of rotation: Oblimin with Kaiser normalization. a. The rotation converged in 9 iterations.

EFA of the Assessment scale

A KMO index of .95 was identified, and Bartlett's test of sphericity yielded a value of $X^2(253) = 10,014.52$, $p < .001$, indicating that the correlation matrix is suitable for conducting a factor analysis. Using Horn's parallel analysis, it was determined that the optimal number of factors for the factorial solution is four. The Eigenvalue criterion also suggests that the optimal solution consists of four factors; therefore, the analysis was conducted with four factors (Table 6).

Table 6

Iterative Process for Improving the Factorial Solution of the Assessment Scale

Solution No.	Items	Factors	Explained variance	Detected issues	Action
1	23	4	64.07	Items with cross-loadings: 1–2–4–6	Remove items 1–2–4–6
2	19	4	64.87	Items with cross-loadings: 15–19–21–22–23	Remove items 15–19–21–22–23
3	14	2	56.21	No issues	

Table 7 presents the final factorial solution of the Assessment scale, which grouped the initial four subdimensions into two factors. These factors explain 56.21% of the variance. The first factor, *Self-judgment*, comprises items SA3, SA5, SA7, SA8, SA9, SA10, SA11, SA12, and SA20. The second factor, *Self-motivation*, comprises items SA13, SA14, SA16, SA17, and SA18.

Table 7

Factorial Solution of the Assessment Scale

Items	Factors	
	Self-judgment	Self-motivation
SA12	.93	

SA7	.90	
SA8	.90	
SA9	.82	
SA5	.73	
SA11	.70	
SA20	.63	
SA3	.60	
SA10	.60	
SA14		.77
SA13		.76
SA18		.72
SA17		.69
SA16		.64

Note. Method of extraction: Unweighted least squares. Method of rotation: Oblimin with Kaiser normalization. The rotation converged in 3 iterations.

CFA of the SRL Questionnaire

A third-order CFA was conducted to assess the model fit, considering the dimensions and the general factor. Table 8 presents the fit results for each model analyzed.

Table 8

Fit Indices of the CFA for the SRL Questionnaire

Models	X ²	X ² / gl	IFC	TLI	SRMR	RMSEA
Planning scale	465.10 (125)	3.72*	.93	.92	.04	.07
Execution scale	210.79 (51)		.95	.93	.05	.07
Assessment scale	186.19 (34)	5.48*	.95	.94	.04	.09
Self-regulation Three Factors	1197.3 (652)	1.84*	0.88	0.87	0.06	0.063
Self-regulation Three	996.7 (652)	1.53*	0.92	0.92	0.06	0.05

Factors c/err
correl.

Note. * $p < .001$; MLR estimator.

For the Planning scale, the analysis showed a value of $X^2 (125) = 465.1$, indicating discrepancies between the model and the data. However, it is important to note that the chi-square value can be sensitive to sample size (Kline, 2016). The X^2/df ratio was 3.72, which falls within an acceptable range (Byrne, 2010). The CFI and TLI fit indices indicate a good model fit (Hu & Bentler, 1999). Similarly, the SRMR also demonstrates a good model fit (Kline, 2016). The RMSEA was .068, suggesting a reasonable fit (Browne & Cudeck, 1993).

For the Execution scale, the chi-square value was $X^2 (51) = 210.789$, and the fit indices were CFI = .95 and TLI = .93, indicating excellent model fit (Hu & Bentler, 1999). The SRMR was .047, showing that the model's residuals were small, and the RMSEA was .07, which is considered an acceptable fit (Browne & Cudeck, 1993).

For the Assessment scale, the chi-square value of $X^2 (34) = 186.19$ indicated discrepancies, and the X^2/df ratio was 5.48, which could suggest fit issues (Kline, 2016). However, the CFI and TLI were .95 and .94, respectively, indicating good fit (Hu & Bentler, 1999). The SRMR was .04, reflecting small residuals, while the RMSEA was .09, suggesting that the model fit could be improved (Browne & Cudeck, 1993).

The Three-Factor Self-Regulation Model presented a chi-square value of $X^2 (652) = 1197.3$, with an X^2/df ratio of 1.84, indicating good fit (Byrne, 2010). However, the CFI and TLI indices were .88 and .87, respectively, suggesting that the model did not reach the desired threshold of .90 (Hu & Bentler, 1999). The SRMR was .06, indicating acceptable fit, and the RMSEA was .06, suggesting reasonable fit. Therefore, it was necessary to re-specify the model by considering correlations between item errors. These correlations were identified through modification indices. The items with correlated errors were as follows: SA13~SA14, SA3~SA5, SA7~SA8, PLA2~PLA4, PLA1~PLA3, EJ9~EJ10, and EJ11~EJ12. After this adjustment, the Three-Factor Self-Regulation Model showed a significant improvement in fit. The final model is a correlated three-factor structure, composed of Planning, Execution, and Assessment as first-order latent variables. Although a third-order model was initially tested, the best fit was achieved with the correlated model, without assuming a hierarchical structure. This configuration reflects three distinct but interrelated components of SRL.

Reliability Analysis of the SRL Questionnaire

The results regarding the reliability of the questionnaire can be found in Appendix 3, which presents Cronbach's α coefficients, and also includes McDonald's ω coefficients to provide a more robust assessment of internal consistency reliability. Adequate consistency indices were identified for the Planning scale, ranging from $\alpha = .74$ to $\alpha = .87$. For the Execution scale, the levels of internal consistency were also adequate, ranging from $\alpha = .78$ to $\alpha = .86$. The Assessment scale showed high internal consistency, with values ranging from $\alpha = .83$ to $\alpha = .89$. The final version of the questionnaire can be found in Appendix 4.

Discussion

This study provides evidence on the validity and reliability of a questionnaire designed to measure SRL in higher education BL contexts. Evaluating students' perceptions of their SRL strategies in contemporary higher education emphasizes the importance of incorporating new and specific behaviors beyond those outlined by previous SRL theories. These behaviors are tailored to meet the demands of a BL education model, which increases the complexity of the construct by introducing subdimensions for each of them, providing a more precise understanding of what students must do to self-regulate their learning in these settings.

Factorial Validity and Model Fit

The analyses indicate that the questionnaire has a well-defined factorial structure, with subdimensions that adequately reflect the theoretical constructs of SRL stages. The elimination of items with cross-loadings or low factor loadings was necessary to optimize the model. This is reflected in the high fit indices obtained in the CFA. The factors in each scale are consistent with prior literature, demonstrating that SRL is a multifaceted construct, reflected in time organization and management, effective study preparation and the establishment of clear learning purposes (Panadero, 2017; Zimmerman & Schunk, 2011).

Planning Scale

The scale explains 55.44% of the variance and encompasses dimensions such as *Time management*, *Study environment preparation*, and *Learning purposes*. These dimensions align with the fundamental processes of the planning stage in SRL theory (Zimmerman, 2000), which is characterized by students' ability to set specific goals, plan their activities and select appropriate strategies to achieve them, elements that have been validated in various psychometric studies (Pintrich, 2004; Wolters & Benzon, 2013). Therefore, these dimensions have also been empirically supported, identifying planning as a critical factor for academic success in BL contexts (Broadbent & Poon, 2015; Dent & Koenka, 2016). Distinguishing behaviors such as time management, study environment preparation, learning purposes, material preparation and study strategy planning allow for a comprehensive approach to aspects students must anticipate for successful study. This approach helps reduce stress and anxiety associated with academic workload (Hinds & Sanchez, 2022; Knezevic et al., 2023; Lobos et al., 2023b). By having greater control over their learning and progress, students feel more confident and less overwhelmed, particularly in BL environments, where research has highlighted that students perceive a greater time demand for virtual activities (Aristovnik et al., 2020; Zhang et al., 2023). In the subdimension *Study environment preparation*, items are associated with characteristics of the physical environment, such as having a comfortable and distraction-free space. This aligns with research emphasizing the importance of having suitable environments for online study (Aguilar Gordón, 2020; Barrientos Oradini et al., 2022). Items related to the quality of the internet connection and technological equipment were removed due to cross-loadings. These items demonstrated greater affinity with the subdimension *Preparation of materials and digital resources*, suggesting that the availability of internet and technological equipment is perceived as a personal responsibility of the student rather than a characteristic of the study environment. This raises questions about the adequacy of spaces provided by universities to meet these needs. There is a consensus that the responsibility for ensuring equitable conditions and equal access lies with educational institutions and/or the State (Aguilar Gordón, 2020; Hodges et al., 2020). Finally, the original subdimension *Management of study goals and purposes* was divided into

two parts: *Study strategy selection*, which includes behaviors such as the search and selection of study strategies, and *Learning Purposes*, which refer to cognitive actions and self-instructions that help students give meaning and utility to what they are about to learn (Díaz Mujica et al., 2019; Lobos et al., 2021).

Execution Scale

The scale demonstrated a clear and robust factorial structure, with an explained variance falling within the ranges considered appropriate for psychological measurement instruments. In the final iteration of the factor analysis, no significant fit issues were identified, suggesting that the underlying structure of the Execution construct is well-defined and consistent with the observed data (Byrne, 2016). The model fit indices, such as the CFI and the RMSEA, showed values indicating a good fit of the model to the data, which is essential to ensure the instrument's validity (Hu & Bentler, 1999). Furthermore, the high variance explained by the main factors reinforces the instrument's ability to capture the essential dimensions of the Execution construct in the context of SRL (Kline, 2016). The absence of fit issues in the final iteration of the CFA also indicates that the items are highly correlated with their respective subdimensions, minimizing the likelihood of unexplained variance and reinforcing the construct validity of the instrument (Tabachnick & Fidell, 2013).

The subdimension *Personal strategies for self-monitoring* largely retained its original items. These strategies are fundamental for students to take advantage of the flexibility offered by the virtual component, enabling them to self-manage their study through efficient and effective monitoring of their time, study methods and learning strategies. Additionally, they allow students to verify whether they are achieving the expected learning outcomes (Bernardo et al., 2020; Taranto & Buchanan, 2020) and foster an elevated level of awareness about the study process, enhancing the student's ability to manage distractions inherent to online environments (Chiu & Hinds, 2022; Jin et al., 2023). As noted by Otazú López and collaborators (2022), the same technology that facilitates online education can also be a source of distraction, with notifications from social media, emails and other applications interrupting the study flow. While multitasking may seem efficient, it can decrease concentration and the quality of learning (Geçer & Bağcı, 2022; Otazú López et al., 2022). Students may feel tempted to engage in other activities during virtual classes, reducing their attention and comprehension. This highlights the importance of task checklists, learning verification and seeking additional materials as central elements in the execution stage.

In the subdimension *Social strategies for self-monitoring*, all remaining items relate to peer interaction, emphasizing the critical role peers play in the execution phase. While the importance of social support in learning is widely recognized (Fraile et al., 2020; Khan et al., 2023), peers also serve as points of comparison, offering a distinct source of information beyond social support. For example, if a student observes that their peers have already reviewed a material, this signals they are falling behind and need to catch up. Similarly, if they notice their peers share the same doubts, they may interpret that it is not an individual issue, making it easier for them to seek help.

Assessment Scale

In the first factor, *Self-judgment*, the original subdimension *Evaluation of study strategies*

absorbed two items from the other original subdimension *Evaluation of study environment and materials*. These items were more broadly worded and encompassed the content of others that were removed due to low loadings. This indicates that students place greater emphasis on evaluating their learning strategies and study methods and, to a lesser extent, on the physical space and study environment.

The second factor, which corresponds to the *Self-motivation* subdimension, only had one item removed due to low loading. The inclusion of behaviors at this stage, associated with affective-motivational factors, highlights the challenge students face in BL environments to stay motivated and organized without the constant structure of in-person classes or the recognition and encouragement that a teacher might provide (Besser et al., 2022; Chiu & Hinds, 2022; Guppy et al., 2022). Self-motivation strategies aimed at encouraging oneself and setting aside negative thoughts are essential to sustain students' efforts in overcoming obstacles. Positive motivation and a constructive mindset help maintain persistence, reduce stress and increase self-confidence, which in turn enhances academic performance and the ability to overcome challenges (Luján Henríquez & Martín Rodríguez, 2021; Vences Camacho et al., 2023).

Reliability

Reliability indices obtained for the scales are satisfactory, with Cronbach's alpha and omega values greater than .74 in all subscales. Reliability is a critical component in psychometric evaluation, as it ensures that the measurement instrument produces consistent and accurate results over time and across different population groups (DeVellis, 2017). A highly reliable instrument not only allows for a more accurate evaluation of SRL but also ensures that interventions based on its results are more effective and well-grounded (Streiner, 2003).

The internal consistency observed supports the proposed factorial structure of the questionnaire, suggesting that the dimensions are clearly defined and well-differentiated, a crucial aspect for the construct validity of the instrument (Cortina, 1993). Reliability indices reinforce the utility of the questionnaire as a tool for evaluating SRL in higher education settings. The developed questionnaire not only offers a valid and reliable tool to measure SRL but can also be used by professionals to identify areas of strength and need among students, enabling the design of more effective interventions to promote self-regulation.

None of the dimensions distinguish between SRL behaviors in face-to-face and online education contexts, allowing the instrument to also be applicable in e-learning or technology-mediated study environments. Regarding this, the online resources and tools students use to enhance their SRL are already part of their autonomous study processes and are utilized regardless of the modality of their courses.

Previously designed instruments, such as MSLQ (Pintrich et al., 1991), LASSI (Weinstein et al., 1987), OSLQ (Barnard-Brak et al., 2010), and SOL-Q (Jansen et al., 2017), were primarily designed for traditional face-to-face settings or for early stages of online learning and tend to focus on partial dimensions of SRL. More recent tools like the SRL-O (Broadbent et al., 2023) focus mainly on the planning phase and do not fully address the regulatory demands of BL environments. The instrument developed in this study operationalizes SRL in a comprehensive manner, incorporating cognitive, motivational, and emotional components. Moreover, it was developed based on the direct experiences of students engaged in BL contexts,

providing greater contextual validity and theoretical coherence for current hybrid learning scenarios.

Limitations and Recommendations

Response bias toward higher scores may limit the generalization of results to populations with different levels of motivation or experience in BL environments. This bias could be influenced by the fact that all participants belong to a single university and most of them are from the same year, reflecting characteristics of that institution such as its academic culture or the profile of its students. Furthermore, the item elimination process during EFA may have reduced response diversity, potentially losing valuable information about variations in student responses, and limiting the questionnaire's ability to fully capture SRL behaviors across contexts. Also, the use of self-report measures based on retrospective recall may introduce bias and affect the validity of the findings, particularly given the complexity of the SRL construct. Results predominantly reflect data collected from first-year students from the same university, which means that the generalizability of these findings to the broader university population is restricted. Future research should explore the application of the questionnaire in more advanced years and different educational contexts, with more diverse populations to evaluate its generalized validity. Additionally, research should investigate how interventions based on the questionnaire's results can influence the academic success of students in BL environments.

Conclusions

This study provides an instrument easy and quick to administer, enabling the assessment of SRL strategies in BL educational contexts.

Study processes in BL contexts require additional strategies to achieve effective SRL. Therefore, educational institutions should enhance their initiatives to promote SRL among students by incorporating these findings into course designs, encouraging students to develop planning, monitoring and autonomous evaluation strategies.

Moreover, the tools of educational platforms such as Learning Management Systems (e.g., CANVAS, D2L), collaborative work applications (e.g., Microsoft Teams, Google Docs) and others, can be intentionally used to develop developing SRL skills. Specifically, virtual classroom functionalities should be employed to help students organize and track their academic progress. Given that the current job market demands professionals with strong digital competencies, promoting SRL also enhances the reputation and performance of educational institutions by better preparing their graduates for success in their future careers and in life.

Declarations

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Appendix A

Table 1

Description of Subdimensions of the Questionnaire

Dimensions	Sub-dimensions
Planning (64): stage in which the student decides what they want to achieve, how they will approach it, and how they will organize themselves to achieve their learning goals.	1. Time planning (8) 2. Study environment preparation (8) 3. Activity planning (7) 4. Preparation of technological devices (11) 5. Preparation of virtual learning materials (8) 6. Study strategy planning (7) 7. Goal setting (7) 8. Self-motivation (8)
Execution (53): stage in which the student gets actively involved in their learning process, performs the planned activities and applies the chosen strategies to achieve their learning goals.	1. Work approach monitoring (11) 2. Learning achievement monitoring (14) 3. Time and activity organization monitoring (15) 4. Help-seeking strategies (13)
Assessment (37): stage in which the student analyzes to what extent they have achieved their learning goals; the effectiveness of the strategies used and considers how they could improve in future learning situations.	1. Self-judgment (14) 2. Self-reaction and self-satisfaction (23)

Note. In parentheses the number of items developed for each subdimension is presented.

Appendix B

Table 1

Descriptive Statistics of the Items in the Self-Regulation Questionnaire

Dimension	Items	Min	Max	Average	Std. Deviation	Asymmetry		Kurtosis	
						Statistical	Std. Error	Statistical	Std. Error
Planning	PLA1	1	5	4.1	1.1	-1.23	.1	1.13	.21
	PLA2	1	5	4.2	1.0	-1.28	.1	1.26	.21
	PLA3	1	5	4.3	0.9	-1.32	.1	1.50	.21
	PLA4	1	5	4.3	0.8	-1.24	.1	1.59	.21
	PLA5	1	5	4.2	1.0	-1.12	.1	0.87	.21
	PLA6	1	5	4.0	1.0	-.92	.1	0.12	.21
	PLA7	1	5	4.0	1.1	-.80	.1	-0.12	.21
	PLA8	1	5	4.1	1.0	-1.12	.1	0.79	.21
	PLA9	1	5	4.6	0.8	-1.99	.1	3.67	.21
	PLA10	1	5	4.5	0.9	-1.84	.1	3.22	.21
	PLA11	1	5	4.5	0.8	-1.72	.1	2.78	.21
	PLA12	1	5	4.6	0.7	-2.04	.1	4.53	.21
	PLA13	1	5	4.7	0.6	-2.38	.1	6.90	.21
	PLA14	1	5	3.6	1.3	-.41	.1	-0.87	.21
	PLA15	1	5	3.9	1.0	-.72	.1	-0.11	.21
	PLA16	1	5	3.5	1.2	-.39	.1	-0.85	.21
	PLA17	1	5	4.0	1.1	-.92	.1	0.09	.21
	PLA18	1	5	4.0	1.1	-1.05	.1	0.26	.21
	PLA19	1	5	4.0	1.2	-.98	.1	0.10	.21
	PLA20	1	5	4.0	1.2	-.96	.1	-0.03	.21
	PLA21	1	5	3.5	1.3	-.46	.1	-0.88	.21
	PLA22	1	5	4.4	0.9	-1.51	.1	2.39	.21
	PLA23	1	5	4.4	0.9	-1.56	.1	2.45	.21

	EX1	1	5	3.9	1.9	-.94	.1	0.35	.21
	EX2	1	5	3.8	1.1	-.75	.1	-0.21	.21
	EX3	1	5	4.1	1.0	-.93	.1	0.17	.21
	EX4	1	5	4.1	1.0	-.97	.1	0.14	.21
	EX5	1	5	4.0	1.0	-.86	.1	0.20	.21
	EX6	1	5	4.1	1.0	-1.02	.1	0.52	.21
	EX7	1	5	3.7	1.4	-.66	.1	-0.86	.21
	EX8	1	5	3.6	1.0	-.35	.1	-0.44	.21
	EX9	1	5	4.4	0.8	-1.35	.1	1.72	.21
	EX10	1	5	4.2	0.9	-1.21	.1	1.00	.21
	EX11	1	5	4.3	0.9	-1.26	.1	1.05	.21
Execution	EX12	1	5	4.4	0.8	-1.51	.1	1.99	.21
	EX13	1	5	4.0	1.1	-1.07	.1	0.44	.21
	EX14	1	5	4.1	1.1	-1.15	.1	0.72	.21
	EX15	1	5	3.9	1.2	-0.88	.1	-0.08	.21
	EX16	1	5	3.9	1.2	-0.77	.1	-0.52	.21
	EX17	1	5	4.1	1.1	-0.96	.1	-0.02	.21
	EX18	1	5	4.1	1.0	-0.91	.1	0.03	.21
	EX19	1	5	3.4	1.4	-0.40	.1	-1.05	.21
	EX20	1	5	3.5	1.3	-0.40	.1	-0.92	.21
	EX21	1	5	3.5	1.3	-0.44	.1	-0.86	.21
	EX22	1	5	3.5	1.4	-0.46	.1	-0.98	.21
	EX23	1	5	3.5	1.2	-0.48	.1	-0.81	.21
	EX24	1	5	3.6	1.2	-.057	.1	-0.61	.21
	EX25	1	5	4.2	1.0	-1.24	.1	1.03	.21
Assessment	SA1	1	5	3.6	1.2	-0.60	.1	-0.59	.21
	SA2	1	5	3.7	1.2	-0.69	.1	-0.33	.21

	SA3	1	5	4.0	1.2	-1.02	.1	0.16	.21
	SA4	1	5	3.8	1.1	-0.76	.1	-0.14	.21
	SA5	1	5	4.0	1.1	-0.95	.1	0.05	.21
	SA6	1	5	4.0	1.05	-1.08	.1	0.74	.21
	SA7	1	5	4.0	1.1	-1.02	.1	0.39	.21
	SA8	1	5	4.0	1.1	-0.95	.1	0.06	.21
	SA9	1	5	4.0	1.1	-1.03	.1	0.41	.21
	SA10	1	5	3.7	1.2	-.62	.1	-0.50	.21
	SA11	1	5	4.1	1.1	-1.10	.1	0.60	.21
	SA12	1	5	4.0	1.1	-0.97	.1	0.19	.21
	SA13	1	5	3.9	1.3	-0.79	.1	-0.64	.21
	AA14	1	5	3.6	1.3	-0.52	.1	-0.98	.21
	SA15	1	5	4.0	1.1	-1.05	.1	0.33	.21
	SA16	1	5	3.8	1.2	-0.73	.1	-0.24	.21
	SA17	1	5	3.3	1.3	-0.25	.1	-0.92	.21
	SA18	1	5	3.9	1.1	-.85	.1	0.07	.21
	SA19	1	5	4.0	1.0	-1.02	.1	0.65	.21
	SA20	1	5	4.4	0.8	-1.44	.1	2.32	.21
	SA21	1	5	4.1	1.0	-0.97	.1	0.52	.21
	SA22	1	5	4.2	0.9	-1.17	.1	1.31	.21
	SA23	1	5	4.0	1.0	-1.00	.1	0.39	.21

Appendix C

Table 1

Internal Consistency of the SRL Questionnaire

Dimensions	Alpha	Omega
Time management	.87	.86
Study environment preparation	.86	.84
Learning purposes	.83	.84
Preparation of materials and digital resources	.74	.73
Study strategy selection	.84	.83
Planning scale	.92	.91
External parameters for self-monitoring	.86	.87
Personal strategies for self-monitoring	.83	.83
Social strategies for self-monitoring	.78	.81
Execution scale	.87	.89
Self-judgment	.89	.89
Self-motivation	.83	.84
Assessment scale	.89	.91

Appendix D

Questionnaire for Self-regulated Learning in Blended or Technology-Mediated Learning Environments in Higher Education

Instruction: Below you will find a series of statements regarding how you organize and carry out your study in learning environments that combine face-to-face and virtual activities. Read each statement carefully and indicate how frequently you perform that action when studying.

To respond, use the following 1-to-5 scale, where 1 means ‘Never’ and 5 means ‘Always’:

1 = Never | 2 = Almost never | 3 = Sometimes | 4 = Almost always | 5 = Always

Respond according to your actual experience. There are no right or wrong answers.

Dimensions and subdimensions of the scale

Planning: Set of actions undertaken prior to the start of studying, through which the student organizes, anticipates, and establishes the necessary conditions for effective learning. This includes defining learning objectives, preparing the physical and virtual environment, managing time, selecting study strategies, and preparing materials and digital resources.

Subdimension	Definition	Original version in Spanish	Reference translation in English
		“Antes de comenzar mi estudio, yo...”	“Before I start studying, I...”
Learning purposes	Actions through which the student sets personal goals and reasons to guide and motivate their study.	Me digo a mí mismo que seré capaz de realizar la actividad con éxito. Busco una razón para que mi estudio sea importante. Me digo a mí mismo que soy capaz de comprender lo que me van a enseñar. Busco una razón para que mi estudio sea útil.	I tell myself I’ll be able to complete the activity successfully. I look for a reason to make my study important. I tell myself I’m capable of understanding what I’m going to be taught. I look for a reason to make my study useful.
Study environment preparation	Actions taken by the student to organize the physical and virtual environment in which they will study.	Busco un sitio tranquilo para estudiar. Busco un lugar sin distracciones para estudiar. Busco un espacio cómodo para estudiar.	I look for a quiet place to study. I look for a place without distractions to study. I look for a comfortable place to study.
Time management	Actions undertaken by the student to organize the time to	Hago una lista detallada de las actividades académicas que necesito realizar.	I make a detailed list of the academic activities I need to complete.

	be devoted to academic activities.	Planifico mi tiempo para atender mis compromisos académicos. Hago un horario para organizar mi tiempo de estudio. Planeo en qué orden realizaré mis actividades académicas.	I plan my time to attend to my academic commitments. I make a schedule to organize my study time. I plan the order in which I'll do my academic activities.
Study strategy selection	Identification and selection of learning methods or techniques suited to the characteristics of the task and the student's prior experience.	Busco estrategias de estudio que puedan ayudarme a aprender más. Evalúo cuál es la mejor forma de estudiar. Pienso en qué estrategias de aprendizaje me han funcionado antes que sean similares a los que enfrentaré.	I look for study strategies that can help me learn more. I evaluate the best way to study. I reflect on learning strategies that have worked for me in similar types of studies to what I'll be facing.
Preparation of materials and digital resources	Actions carried out by the student to prepare and organize learning materials, as well as the technological tools and resources required for studying.	Me aseguro de contar con el software/programa adecuado para mi estudio (programa instalado, licencias, claves, etc.). Considero el almacenamiento en la nube para respaldar y acceder a mis recursos en todo momento. Me aseguro de tener a mano todo el material que pueda necesitar antes de empezar a estudiar. Considero recursos en línea que puedan ser de utilidad para mi estudio.	I verify I have the necessary study software (installed programs, licenses, passwords). I consider cloud storage to back up and access my resources at all times. I make sure to have all the materials I might need on hand before starting to study. I consider online resources that might be useful for my studies.
Execution: Encompasses the strategies and behaviors implemented by the student while carrying out academic activities, aimed at monitoring and regulating their own learning. It includes the use of personal, social, and external parameter comparison strategies to track progress, identify difficulties, and make real-time adjustments.			
Subdimension	Definition	Original version in Spanish	Reference translation in English
		“Mientras realizo mi estudio, yo...”	“While I study, I...”

Personal strategies for self-monitoring	Individual behaviors to monitor progress, identify difficulties, and make adjustments to one's study approach.	Reviso mi lista de tareas por hacer.	I review my to-do list.
		Ajusto mi forma de trabajo cuando me doy cuenta de que no está respondiendo a mis necesidades de estudio.	I adjust my way of working when I realize it's not meeting my study needs.
		Busco material en línea que me ayude a comprender mejor los temas que estoy estudiando.	I look for online material that helps me better understand the topics I'm studying.
		Reviso materias anteriores que me ayuden a estudiar. Hago ejercicios para comprobar que estoy aprendiendo. Me hago preguntas sobre la materia para saber si estoy aprendiendo.	I review previous subjects that help me study. I do exercises to make sure that I'm learning. I ask myself questions about the material to know if I'm learning.
Social strategies for self-monitoring	Interaction with peers to request, offer, or exchange academic support aimed at enhancing learning.	Comparto mis conocimientos con compañeros cuando domino un tema.	I share my knowledge with classmates when I master a topic.
		Pido ayuda a mis compañeros cuando me doy cuenta de que no logro aprender.	I ask my classmates for help when I realize I'm not able to learn.
		Contacto a mis compañeros para resolver dudas de mi estudio.	I contact my classmates to resolve study doubts.
		Busco ayuda cuando me doy cuenta de que necesito apoyo.	I seek help when I realize I need support.
External parameters for self-monitoring	Comparison of one's own progress and outcomes with indicators of peers' performance and progress.	Reviso como avanzan mis compañeros en sus estudios para estimar mi propio avance.	I check how my peers are advancing in their studies to estimate my own progress.
		Voy comparando mis aprendizajes con los de mis compañeros/as para evaluar si estoy aprendiendo. Comparo mis calificaciones (notas) con las de mis compañeros	I compare my learning with that of my classmates to assess if I'm learning. I compare my grades (scores) with those of my

para evaluar mi rendimiento. Comparo si las dificultades que experimento en mi aprendizaje son similares a las de mis compañeros.	classmates to evaluate my performance. I compare if the difficulties I experience in my learning are similar to those of my classmates.

Assessment: Refers to the actions taken by the student upon completing their study to evaluate their performance and outcomes. This includes self-assessment of the process and the strategies employed (self-judgment), as well as the use of self-motivation resources that support sustained effort and improvement in future learning.

Subdimension	Definition	Original version in Spanish	Reference translation in English
		“Cuando he terminado mi estudio, yo...”	“When I’ve finished studying, I...”
Self-judgment	Actions undertaken by the student to evaluate their study process and learning outcomes.	Busco espacios que cuenten con mejores condiciones (infraestructura, internet, equipamiento u otro) cuando evalúo que los utilizados fueron deficientes. Evalúo si el entorno para mi estudio fue el más apropiado. Evalúo si mi forma de estudio fue la más adecuada. Evalúo si mi organización de actividades fue exitosa. Evalúo si la planificación del tiempo fue la correcta. Solicito retroalimentación para obtener una comprensión más clara de mi desempeño académico. Vuelvo a revisar el material de estudio para mejorar mi aprendizaje, aclarar dudas y/o corregir errores.	I look for spaces with better conditions (e.g., infrastructure, internet, equipment) when I assess that the ones I used were deficient. I evaluate if my study environment was the most appropriate. I evaluate if my study method was the most appropriate. I assess if my activity organization was successful. I evaluate whether my time planning was correct. I request feedback to gain a clearer understanding of my academic performance. I re-review study material to improve my learning, clarify doubts, and/or correct mistakes.

		Evalúo si la(s) estrategia(s) de estudio que utilicé fueron las más adecuadas. Evalúo si obtuve la calificación (nota) que esperaba	I evaluate whether the study strategy(ies) I used were the most appropriate. I assess whether I obtained the score (grade) I expected.
Self-motivation	Strategies aimed at strengthening personal motivation, maintaining effort, and the willingness to continue learning.	Me auto felicito cuando he logrado mis metas de estudio. Me auto premio cuando he logrado un buen aprendizaje. Interpreto mis fallos en mi estudio como una opción de mejora. Aparto pensamientos negativos sobre mí mismo cuando no he logrado un buen aprendizaje. Me doy ánimo para continuar estudiando cuando no alcanzo las metas de aprendizaje que me he propuesto.	I praise myself when I've achieved my study goals. I reward myself when I've achieved good learning. I interpret my study failures as an opportunity for improvement. I set aside negative thoughts about myself when I have not achieved good learning outcomes. I encourage myself to keep studying when I fail to reach my learning goals.

Cognitive Demands and Course Pedagogical Design: Understanding Success in Online Learning Environments

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Abstract

The COVID-19 pandemic catalyzed a global shift to online learning, highlighting both the challenges and opportunities of this mode of education. Despite extensive research on student performance in online courses, there remains a lack of focus on the pedagogical characteristics that influence educational outcomes. This study investigates the relationship between the pedagogical design of online courses and academic performance in higher education, with particular emphasis on Universal Design for Learning (UDL) principles and cognitive complexity levels defined by Bloom's taxonomy. Data were collected from 661 students across 22 online courses, analyzing demographic variables, pedagogical features, and students' interaction patterns on course platforms. Multiple regression models revealed that both demographic and pedagogical characteristics significantly predict online course grades, while student interaction patterns did not. Additionally, tasks requiring higher-order thinking skills were associated with lower grades, emphasizing the need for carefully scaffolded support in online environments. The study also found that UDL attributes may function differently across achievement levels, being less beneficial—or differently aligned—for high-achieving students. These findings underscore the importance of tailoring online course design to diverse learner needs and suggest a balance between accessibility and cognitive complexity. This research provides actionable insights for improving online learning environments and advancing evidence-based educational practices.

Keywords: Online learning, universal design for learning, Bloom's taxonomy, cumulative GPA

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In recent years, education systems have invested major efforts in designing new learning environments, with emphasis on the integration of technological means (Collins & Halverson, 2018). The outbreak of the COVID-19 pandemic in the spring of 2020 spawned a revolution in education systems across the globe by necessitating a comprehensive shift to remote learning for all students (Dietrich, 2020; Fewella, 2023). Despite the complexity of comparing online learning that was planned in advance to online learning necessitated by an emergency, the ongoing pandemic underscored the inherent difficulties when learners interacted with learning materials, lecturers and their fellow students online, as well as the decrease in sense of belonging to the academic institution among students and lecturers alike (Baxter & Haycock, 2014; Seifert & Bar-Tal, 2023). The situation also highlighted the inequality among learners, for example with respect to the physical conditions in their homes (Gillis & Krull, 2020).

In conjunction with the difficulties, online learning also opened new horizons and educational opportunities in academia. From the perspective of organizing the learning, the online environment provides flexibility and accessibility in time and place (Xie et al., 2020). From the didactic perspective, the online learning environment offers diverse possibilities for visual or auditory presentations (e.g., Olsson et al., 2016). The technological basis of online learning provides the ability to organize and document discussions to facilitate collaboration in constructing knowledge (Simpson, 2016) and in monitoring students' progress (Saghafi et al., 2014). In addition, the use of information and communications technology can support a variety of constructivist teaching strategies to develop 21st century skills (Zhu, 2008) and can promote communication between students, lecturers, and colleagues through forums and social groups, thanks to its flexible scheduling capabilities (Cheng & Chau, 2014). Consequently, understanding the pedagogical design of such environments—particularly in terms of accessibility and cognitive complexity—has become a central question for online higher education.

At the same time, alongside new educational challenges, the general mobilization for remote learning that took place during the COVID-19 pandemic launched an age of creativity and abundance in the field of pedagogical design of online learning environments. In addition, the status of online learning shifted from an alternative that could be rejected to a given situation that is unavoidable under certain circumstances. Indeed, the pedagogical improvement offered by online learning is not a matter of choice but rather a present need. Consequently, systematic characterization of online learning environments and formulation of institutional policy for online teaching and learning are of utmost importance.

Although extensive research has examined factors influencing educational outcomes, only a limited number of studies have systematically analyzed the *pedagogical quality* of online learning environments. Recent works published in *Online Learning Journal* have contributed valuable insights—such as the quantitative analysis of higher-order thinking development (Page, 2022) and studies on UDL implementation and instructor-driven design (Altowairiki, 2023; Underhill & Turk, 2024). Nevertheless, there remains a need for large-scale, integrative modeling that jointly examines multiple pedagogical dimensions—such as Universal Design for Learning and cognitive complexity—across diverse courses and disciplines.

The impact of integrating technology into education varies in accordance with type of technology, type of pedagogy, learners' ages, and areas of study (Jeong et al., 2019).

Further research is needed to better understand the factors affecting the online learning experience in higher education (Nortvig et al., 2018; Rodrigues et al., 2019). Lai and Bower (2019) systematically reviewed 365 research papers examining the use of technology in education. They found that most studies examined learners' academic achievements, viewpoints, learning styles, and motivation, whereas only 11% focused on pedagogical characterization. Their findings underscore the importance of pedagogical research to examine online learning environments in academia.

Despite changes in the academic world since the outbreak of the COVID-19 pandemic, academic institutions have not yet formulated any distinct policy for designing online courses, and academic lecturers are clearly having difficulty implementing optimal pedagogical practices in online teaching (Reich et al., 2020). In response to this gap, this research offers an examination of online college learning environments with the goal of understanding the relationship between the pedagogical components of online courses and their educational outcomes. The findings can make an important contribution to promoting evidence-based education and to understanding best practices or what works in education (Borman et al., 2003; Reynolds et al., 2014). The results can also help in designing an explicit policy for online courses and in promoting the professional development of the academic staff. To inform such policy and practice, a deeper theoretical understanding of pedagogical design in online environments is required. Building on this growing reliance on online learning, there is a pressing need to examine not only whether students succeed in digital environments, but how the pedagogical design of those environments shapes their learning outcomes. Two well-established frameworks—Universal Design for Learning (UDL) and Bloom's taxonomy—offer complementary perspectives for analyzing the quality and cognitive demands of online courses. The current study therefore investigates how these pedagogical dimensions, together with student characteristics, predict success in online higher education.

Theoretical Background

Characterization and Assessment of Online Learning Environments

Over the years, numerous studies have examined the effectiveness of online learning environments using a variety of indicators, most often through survey-based tools (Pardino et al., 2018). Early evaluations typically compared student achievement in online versus face-to-face courses (e.g., Jayachithra, 2020), while later research increasingly emphasized learners' perspectives through measures such as satisfaction, engagement, and perceived learning (Caspi & Blau, 2008; Malkawi et al., 2020; Rovai et al., 2009). These studies have provided valuable insights into how students experience online education but have focused mainly on outcome and interaction indicators rather than on the pedagogical design itself. Within the broader socio-cognitive perspective, several models have characterized the quality of online learning through patterns of interaction among learners, instructors, and materials (Nortvig et al., 2018). The Community of Inquiry (CoI) framework (Garrison et al., 2000) has been particularly influential in describing the cognitive, social, and teaching presence that underlie meaningful online learning. However, while such models advance understanding of communication and engagement, they do not directly address the instructional and cognitive design features that shape learning processes.

More recently, researchers have proposed integrative frameworks for analyzing learning environments through multiple pedagogical dimensions—such as educational principles, higher-order thinking, and learning psychology (Miedijensky et al., 2021; Sasson, 2019; Sasson et al., 2022). These approaches emphasize systematic characterization of

instructional practices and their relation to student outcomes, offering a foundation for the current study's focus on pedagogical quality in online course design.

Universal Design for Learning – UDL

Universal Design for Learning (UDL) is a pedagogical framework aimed at creating flexible teaching and learning methods that cater to the diverse needs of students, including those with and without special needs, in various educational contexts (Black et al., 2014; Capp, 2017; CAST, 2017; Evmenova, 2018). The concept is rooted in principles from architecture, where environments are designed to ensure accessibility for all individuals, regardless of their physical abilities or unique needs (Rao & Tanners, 2011).

UDL is built upon three core principles: (1) providing multiple means of engagement, (2) offering multiple means of knowledge representation, and (3) enabling multiple means of expression for understanding (Capp, 2017; CAST, 2017; Evmenova, 2018). These principles align with key components of the cognitive learning process, involving affective networks responsible for motivation, recognition networks for processing and analyzing information, and strategic networks for planning and executing actions (Dell et al., 2015; Robinson & Wizer, 2016).

Technology plays a significant role in supporting UDL by providing tools for presenting knowledge in diverse ways and enabling students to demonstrate understanding through various modalities. Research has shown that UDL-based interventions—such as online and blended learning, multimedia resources, social media platforms, and interactive websites—are effective in fostering diverse learning abilities (Hall et al., 2015; Kennedy et al., 2014; King-Sears et al., 2015). Recent empirical and institutional evaluations have shown the potential benefits of UDL-informed design in higher education (e.g., Garrad & Nolan, 2022; Altowairiki, 2023).

A related concept is Universal Design for Instruction (UDI), which focuses on curriculum and instructional strategies that offer equal learning opportunities to all students. UDI emphasizes additional principles such as promoting varied methods of instructional use, tolerance for error, fostering a community of learners with active communication, and creating an inclusive instructional climate that maintains high expectations for all students (McGuire & Scott, 2006).

Bloom's Taxonomy: A Framework for Cognitive Complexity

First introduced by Benjamin Bloom in the 1950s, Bloom's Taxonomy provides a foundational framework for classifying cognitive processes in learning (Bloom, 1964). The taxonomy is organized into six hierarchical levels, each reflecting a progressively complex form of cognition: knowledge, comprehension, application, analysis, synthesis, and evaluation. The knowledge level emphasizes the recall of factual information or previously acquired concepts, while comprehension focuses on grasping the meaning of information and explaining ideas. Application involves utilizing acquired knowledge in novel contexts, and analysis requires breaking down complex ideas into their components to explore relationships. Synthesis entails combining elements to create new ideas, and evaluation requires critical judgment based on specific criteria or standards. This hierarchy enables educators to promote higher-order thinking skills (HOTS) and deepen student understanding beyond mere memorization (Anderson & Kathwohl, 2001).

Bloom's Taxonomy is widely recognized for its effectiveness in distinguishing between tasks requiring rote memorization and those involving advanced cognitive functions such as application, analysis, or evaluation (Boeren & Iniguez-Berrozpe, 2022; Drakpa et al.,

2021; Muhayimana et al., 2022). Nevertheless, the taxonomy has been subject to criticism, particularly regarding the challenges of categorizing tasks into discrete levels. Scholars have noted the difficulty in distinguishing adjacent levels, such as comprehension versus application (Athanassiou & McNett, 2003). Bloom himself acknowledged this ambiguity, recognizing the overlapping nature of cognitive tasks and the complexity of accurately assigning them to specific levels.

Building on the pedagogical frameworks of UDL and Bloom's taxonomy, this study examines how these principles manifest in the design of online courses in higher education. By focusing on the diversity of teaching methods, cognitive complexity levels, and engagement strategies, the study aims to explore their role in academic performance. Although previous research has addressed each of these frameworks separately, few studies have integrated UDL and Bloom's taxonomy within a unified, quantitative coding framework for evaluating course design. The present study therefore employs these two models as the conceptual foundation for the coding and analytical procedures described in the Methods section.

Research Questions

- a) What are the predictors of success in an online course, as examined through three models: (1) student demographic characteristics, (2) pedagogical characteristics of the course, and (3) students' login patterns on the course platform?
- b) How is cumulative GPA related to online course performance, and to what extent do pedagogical characteristics of the course and students' login patterns moderate this relationship?

Methods

The courses included in the study were selected based on a list of all online undergraduate courses offered during the academic year across three faculties at the institution. This list, comprising 72 courses, was obtained from the college's academic administration. All instructors teaching these courses were contacted and informed of the study's objectives and voluntary nature. Ultimately, 22 instructors provided informed consent, and their courses were included in the research.

All 22 courses were part of undergraduate programs across various disciplines, including education, social sciences, humanities, and science and technology. The courses varied in scope, including both introductory and content-specific courses, and were delivered in asynchronous or blended formats. The college does not have a formal policy or set of guidelines for online course design, nor does it enforce a standardized model for pedagogical practice in online learning. While no mandatory training was provided to instructors, those who sought pedagogical or technical support were able to receive assistance from the college's Center for Innovation in Teaching and Learning. Universal Design for Learning (UDL) is not formally promoted at the institutional level and is not embedded in institutional policy or training programs. As such, the inclusion of UDL-related features in the courses examined reflects individual instructors' pedagogical choices rather than institutional directives.

Participants included 661 students in 22 online courses. The data provided by the Department of Student Administration at the college showed 338 of the students (51.1%) majored in education and teaching, 223 (33.7%) majored in social sciences and humanities,

and 98 (14.8%) majored in science and technology. Data from two students were not included in this file. With respect to gender, 463 (70%) were women and the rest were men (198, 30%). Moreover, 172 students (26%) were in their first year of academic studies, 182 (27.5%) were in the second year, 249 (37.7%) were in the third year, and 55 (3.8%) were in the fourth year. Data from three students were not included in this file. With respect to ethnicity, 494 (74.7%) of the students were Jewish and 164 (24.8%) were not Jewish. Data from three students were not included in this file. Finally, 98 students (15%) were diagnosed with learning disabilities.

The pedagogical characterization of online courses focused on two key aspects: universal design for learning (UDL) attributes and cognitive complexity levels based on Bloom's taxonomy. Coding of UDL attributes: The analysis of UDL implementation covered all course materials available on the online learning platforms and was based on the three core UDL principles—multiple means of engagement, representation, and expression (Evmenova, 2018). Each dimension was coded on a three-level ordinal scale, reflecting the extent to which pedagogical practices were evident:

(1) *Engagement* – coded as 1 when up to two active-learning practices were identified (e.g., forum discussions, peer review), 2 when three to five were observed, and 3 when more than five were present.

(2) *Representation* – coded according to the variety of ways in which information was presented to students (e.g., text, visual materials, audio/video lectures, infographics).

(3) *Expression* – coded according to the range of modalities students were invited to use to demonstrate learning outcomes (e.g., written papers, oral presentations, creative projects, multimedia submissions).

The overall UDL score for each course reflected the average implementation level across these three dimensions.

Coding of cognitive complexity: Bloom's taxonomy (Anderson & Krathwohl, 2001) was applied to analyze the learning tasks and assignments presented in each course. Each task was reviewed in full, and every question within it was classified according to the six hierarchical levels of cognitive demand—*remember*, *understand*, *apply*, *analyze*, *synthesize*, and *evaluate*—based on the highest level of thinking required for an optimal response. For example:

Application level task: A high school administration seeks to introduce a pedagogical change integrating AI tools in teaching and learning. Refer to the first stage in Lewin's organizational change model and describe it in this context: What problem would initiate the change process? What actions would you take to create motivation for change and reduce resistance?" This task was coded at the *application* level because it requires applying a theoretical model to a concrete case.

Evaluation level task: Students were asked to conduct a self-assessment of their academic writing using a detailed rubric and then reflect on the experience: What conclusions can you draw? What did you learn about self-assessment and about yourself as a learner? Did you identify discrepancies between your self-evaluation and the instructor's assessment, and if so, what might explain them?" This task was coded at the *evaluation* level, the highest cognitive complexity, as it involves critical

reflection, metacognitive reasoning, and evaluative judgment. Each course was assigned the highest cognitive complexity level identified among all its tasks, representing the maximal level of cognitive challenge embedded in the course design.

Together, these coding procedures operationalized pedagogical quality as reflected in both accessibility and inclusivity (UDL) and cognitive demand (Bloom's taxonomy), providing the basis for subsequent statistical analyses.

To ensure reliability, two research assistants were trained to code the pedagogical features of the courses. During the initial phase, they jointly analyzed three courses to establish consistency in their approach. Subsequently, they independently analyzed three additional courses to assess inter-rater reliability, achieving an 83% agreement rate. Following this, each research assistant was assigned responsibility for coding eight courses individually.

Appropriate codes were used to calculate each student's behavioral patterns on the online course's Moodle platform. The focus was on the number of times each student logged into the course site and the characteristics of their learning sequence as reflected in these logins, as assessed on a five-point scale: 0 when a student logged in only once; 1 when a student logged into the course site several times on a given day; 2 when a student logged into the course site several times on consecutive days; 3 when a student logged in without following any organized sequence; and 4 when a student's login sequence was mixed (several days in a row, a break of several days, followed by several days in a row). These patterns were calculated for 16 types of activities that students conducted on the online course website via Moodle: link to a padlet board; PowerPoint presentation; link to an external site; link to the syllabus; blog; forum; list of references; lesson summaries or focused lesson descriptions; submitting an assignment via Moodle; accessing articles or textual information; link to a survey; question sheet; Moodle quiz; questions to prepare for exam or exams from previous years; accessing pictures (non-textual information, maps, charts and the like); external software package that includes a number of videos or text together with an online quiz (Quizz).

Behavioral indicators of student activity were extracted from the learning management system (LMS), including login frequency and sequence, representing the temporal patterns of course participation. These measures were chosen because they provide objective, student-level data that can be directly linked to academic outcomes. Although such indicators do not fully reflect students' psychological engagement or motivational states, they capture meaningful differences in learning behaviors—for example, whether students engage continuously throughout the course or concentrate their learning efforts in short, intensive periods.

In order to link students' demographic characteristics, academic performance, and LMS usage patterns, matching was performed across institutional datasets. Cases with missing demographic, achievement, or LMS data were excluded from the analyses to ensure data integrity and consistency across variables. The final dataset therefore included only students with complete information on all relevant measures.

Coders were granted access to the online course shells with the instructors' explicit consent, solely for the purpose of pedagogical analysis. The review included course materials, assignments, and activity structures, but no identifiable student information (such

as names, discussion posts, or submissions) was recorded. All data were documented in aggregate form, focusing only on pedagogical characteristics relevant to the coding framework, in accordance with institutional ethical approval.

Because instructor participation was voluntary, the final sample of 22 courses reflects those whose lecturers consented to take part in the study. This self-selection may introduce some degree of bias, as participating instructors might differ in their pedagogical interest or openness to innovation. However, the sample includes courses from all three faculties and across diverse disciplinary domains, providing a heterogeneous and reasonably representative picture of online teaching practices within the institution. The goal of the study was not statistical generalization, but rather to identify trends and relationships in pedagogical design across a range of authentic course settings.

Ethical Considerations

The study received approval from the institutional ethics committee, which also granted a waiver of student consent, as the data were drawn from administrative academic records and fully anonymized prior to analysis. One authorized research staff member handled the identifiable dataset to merge academic and LMS information, replaced all student identifiers with non-traceable codes, and deleted the identifiable file after anonymization. Coders accessed the online course shells with instructors' explicit permission for the purpose of pedagogical analysis only and did not view or record any identifiable student submissions or posts. All analyses were conducted using anonymized data in accordance with institutional and national ethical standards for research involving human participants.

Data Analysis

Statistical analyses were conducted using SPSS (version 28). Prior to computing the interaction terms, all continuous predictors were mean-centered to reduce multicollinearity. The assumptions of linearity, normality of residuals, and homoscedasticity were verified through residual plots, histograms, and normal probability (P-P) plots. All assumptions were met within acceptable ranges. Multicollinearity diagnostics indicated that all tolerance values exceeded .40 and VIF values were below 2.5, suggesting no collinearity concerns. The regression models were estimated using the Enter method in three hierarchical steps. Missing data were handled listwise. Effect sizes and change in explained variance (ΔR^2) were examined for each model to evaluate the incremental contribution of the pedagogical and behavioral predictors.

The dataset included students nested within 22 online courses. Because the number of students per course varied and the study's primary focus was on individual-level predictors, all analyses treated students as independent cases. However, it is acknowledged that some degree of non-independence may exist due to shared course contexts. Future research using a multilevel modeling approach could more precisely estimate course-level effects.

Results

To answer the first research question, a multiple regression analysis was conducted to examine the predictors of online course grades (dependent variable) across three models.

Model 1: Demographic Characteristics

The first model included demographic predictors: academic major, year of study, gender, ethnicity, whether student was diagnosed with learning disabilities, and cumulative GPA. This model was statistically significant, $F(6, 274)=3.791, p=.001$ and explained 7.7% of the variance in online course grades (Adjusted $R^2=.056$). Among the predictors, academic major ($\beta=-0.148, p=.014$) and cumulative GPA ($\beta=0.260, p<.001$) were significant contributors.

Model 2: Pedagogical Features of the Course

The second model included the predictors from Model 1 and added pedagogical characteristics: Bloom's taxonomy level, UDL-engagement, UDL-knowledge, UDL-information, number of features, and the synchronous/asynchronous course format. This model was also statistically significant, $F(12, 268)=3.684, p<.001$, explaining 14.2% of the variance in course grades (Adjusted $R^2=.103$). Significant predictors included: Bloom's taxonomy level ($\beta=-0.146, p=.036$); Cumulative GPA ($\beta=0.265, p<.001$); and UDL-engagement ($\beta=-0.188, p=.041$). The inclusion of pedagogical features significantly improved the model ($\Delta R^2=.065, p=.003$).

Model 3: Patterns of Student Interaction with the Online Platform

The third model added variables related to student interaction with the course platform: overall average number of student logins to activities on the course website, and average login sequence pattern. This model was not statistically significant, $F(14, 266)=3.144, p=.943$, and did not explain additional variance beyond Model 2 ($\Delta R^2=.000, p=.943$).

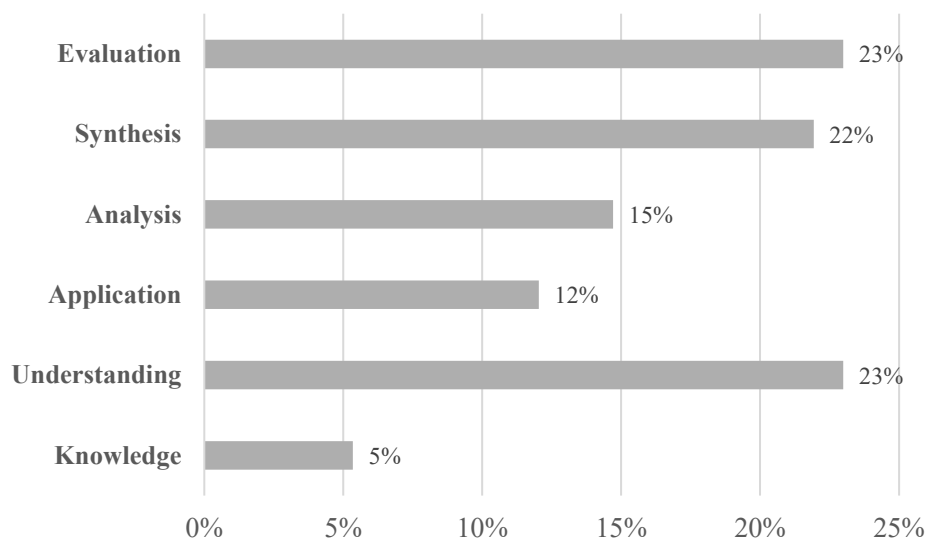
The results indicate that both demographic characteristics and pedagogical characteristics significantly predict online course grades. However, patterns of student interaction with the course platform did not contribute significantly to explaining variance in grades.

A one-way ANOVA was conducted to examine the differences in online course grades across Bloom's taxonomy levels. Levene's test for equality of variances indicated a violation of the assumption of homogeneity of variances, $F(5, 345)=5.650, p<.001$. Therefore, the Games-Howell post hoc test was used for pairwise comparisons.

The ANOVA was significant, $F(5, 345)=3.739, p=.003$, indicating differences in grades among Bloom's taxonomy levels. Pairwise comparisons using the Games-Howell test revealed significant differences: Students scored significantly lower on synthesis tasks ($M=76.84, S.D.=23.85$) compared to application tasks ($M=87.35, S.D.=8.55$), $p=.009$. Grades were also significantly lower on evaluation tasks ($M=79.22, S.D.=14.61$) compared to application tasks, $p=.002$. No significant differences were found between other Bloom's taxonomy levels. These results suggest that tasks requiring higher-order thinking skills, such as synthesis and evaluation, were associated with significantly lower grades compared to application tasks. Figure 1 presents the frequency of the courses according to the highest level in Bloom's taxonomy coded in the learning tasks on the course website.

Figure 1

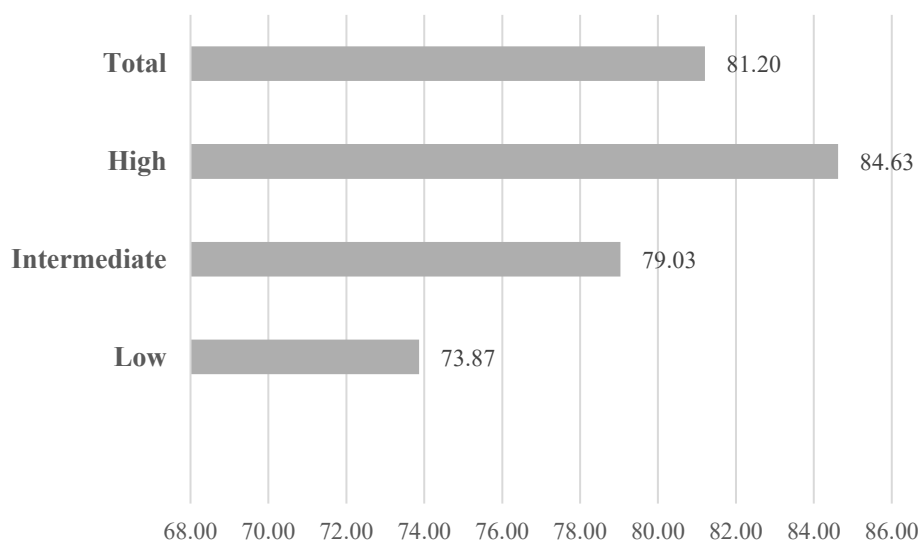
Frequency of Courses According to the Highest Level in Bloom's Taxonomy Coded in the Learning Tasks



An independent-samples t-test was conducted to compare the grades of students in courses with only one active learning strategy versus those with multiple strategies (UDL-engagement). Levene's test indicated a violation of the assumption of equal variances ($p < .001$). Therefore, the results for equal variances not assumed were used. Results showed that students in courses with multiple strategies scored significantly lower ($M = 78.37$, $S.D. = 18.41$) compared to those in courses with only one strategy ($M = 86.24$, $S.D. = 11.99$), $t(347) = 4.821$, $p < .001$. The effect size was calculated using Cohen's d , which indicated a medium effect ($d = 0.492$).

A one-way ANOVA was conducted to examine the differences in online course grades across cumulative academic levels. Levene's test for equality of variances indicated a violation of the assumption of homogeneity of variances, $F(2, 484) = 8.091$, $p < .001$. Therefore, the Games-Howell post hoc test was used for pairwise comparisons.

The ANOVA was significant, $F(2, 484) = 9.050$, $p < .001$, indicating differences in grades among cumulative academic levels. Pairwise comparisons using the Games-Howell test revealed significant differences: Students in low academic level had significantly lower online course grades ($M = 73.87$, $S.D. = 27.29$) compared to students in high level ($M = 84.63$, $S.D. = 16.11$), $p = .020$. Grades were also significantly lower among students in intermediate level ($M = 79.03$, $S.D. = 19.63$) compared to students in high level, $p = .004$. No significant differences were found between students in low and intermediate levels. Figure 2 presents the means for each academic level.

Figure 2*Grade Means in Online Course for Each Academic Level*

To answer the second research question, Pearson's correlation coefficient testing revealed a significant, low, and positive correlation between students' cumulative GPA and their grades in the online course ($r=0.162$, $p<0.001$). The PROCESS micro developed by Hayes (2013) and implemented in SPSS 28.0 was used to examine how the pedagogical characteristics of the online course and the student login patterns to course activities moderate this correlation. In the examination, cumulative GPA was the independent variable and grade in the online course was the dependent variable. The following moderation variables were examined: variety in how instructors present information (UDL-information), variety in how students present knowledge (UDL-knowledge), number of features, cognitive level of tasks according to Bloom's taxonomy, overall average number of student logins to activities on the course website, and average login sequence pattern. Among these variables, three were found to be significant moderators: variety in how instructors present information, variety in how students present knowledge, and number of features. These three variables are manifestations of the UDL principles.

Table 1 depicts the results with respect to the moderating variables found to be significant. As can be seen in Figures 3-5, the relationship between cumulative GPA and online course grade is weak when UDL manifestations are high (indicated by the low slopes of the dashed curves in the three figures), and this relationship strengthens significantly when UDL manifestations are low (indicated by the high slopes of the solid curves in the three figures). Additionally, the figures reveal differences among students at different academic levels in the effect of UDL attributes on their course grade. An increase in the number of features on the course website and an increase in the variety of ways the lecturer presents the information affects an increase in the course grade among students with a low academic level. An opposite trend was found among students at a high academic level. Similar but more moderate effects were found for the diversity in ways of presenting knowledge by the students. These findings highlight the differences in the impact of the pedagogical design of the online course on students at different academic levels.

These moderation findings suggest that the benefits of UDL-related features are not uniform across students. For students with lower cumulative GPA, a rich pedagogical design—featuring diverse materials, presentation formats, and engagement strategies—appears to enhance their course performance. In contrast, for students with higher cumulative GPA, the same features do not offer additional benefit and may even hinder performance, possibly due to redundancy or cognitive overload. The interaction plots (Figures 3–5) visually demonstrate this pattern: The solid line represents students in courses with low levels of UDL features. It shows a steep upward trend, indicating that higher cumulative GPA strongly predicts higher course grades in less pedagogically diverse courses. The dashed line, representing high levels of UDL features, is relatively flat suggesting that in courses with many UDL attributes, students' GPA is less predictive of their actual performance. This flattening of the slope implies that UDL features may serve as a form of scaffolding that levels the playing field for lower-achieving students, reducing the performance gap between students with lower and higher prior achievement. In other words, while high-GPA students tend to succeed regardless of the course design, low-GPA students benefit significantly from thoughtful and inclusive pedagogical strategies. This highlights the importance of aligning course design with learner diversity and offering differentiated support.

Table 1

Moderating Variables in the Relationship Between Cumulative GPA and Grade in the Online Course

Variable	<i>B</i>	Std.Err.	β
Variety in how instructors present information (UDL-information)	47.996	17.523	1.493*
Cumulative GPA	1.225	0.383	0.788*
UDL-information* Cumulative GPA	-0.562	0.209	-1.659*
Variety in how students present knowledge (UDL-knowledge)	40.769	15.449	1.308*
Cumulative GPA	1.107	0.317	0.712**
UDL-knowledge* Cumulative GPA	-0.518	0.183	-1.564*
Number of features	32.729	11.353	1.711*
Cumulative GPA	1.242	0.374	0.801*
Number of features* Cumulative GPA	-0.379	0.136	-1.834*

Note. * $p < .01$, ** $p < .001$

Figure 3

The Level of Diversity in how Instructors present information as a Moderating Variable of the Relationship Between the Student's Cumulative GPA and the Grade in the Online Course

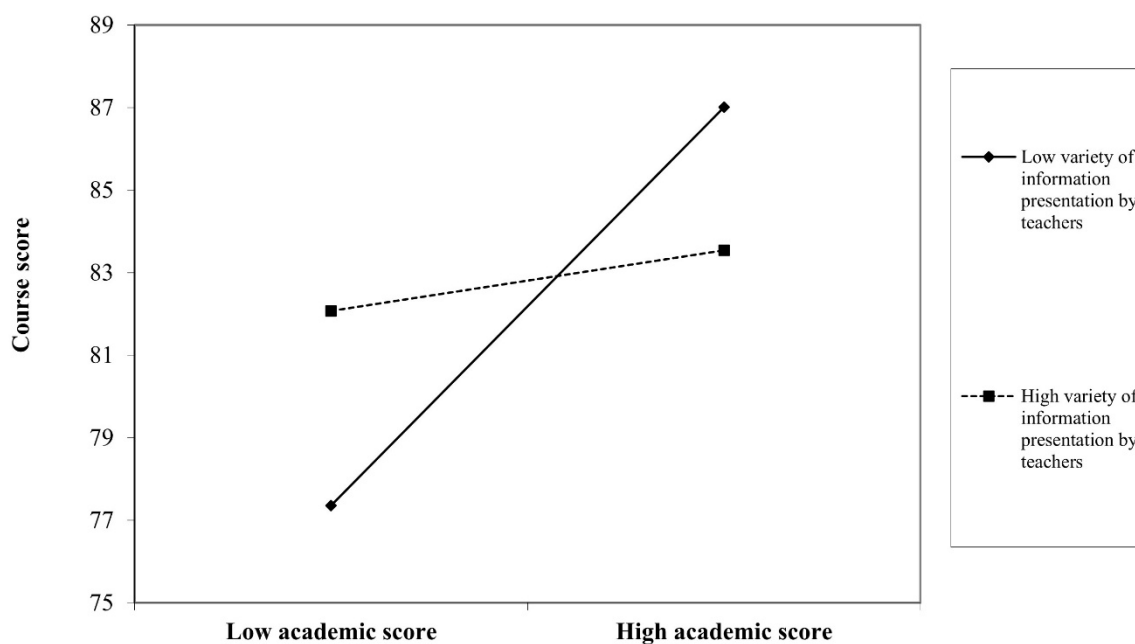


Figure 4

The Level of Diversity in How Students Present Knowledge as a Moderating Variable of the Relationship Between the Student's Cumulative GPA and the Grade in the Online Course?

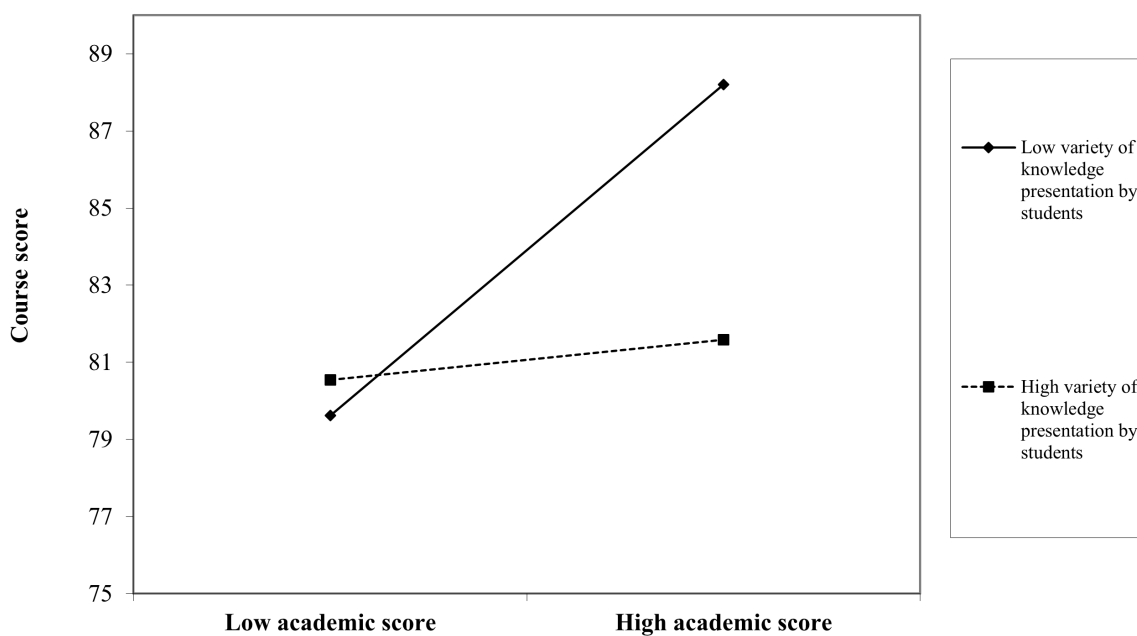
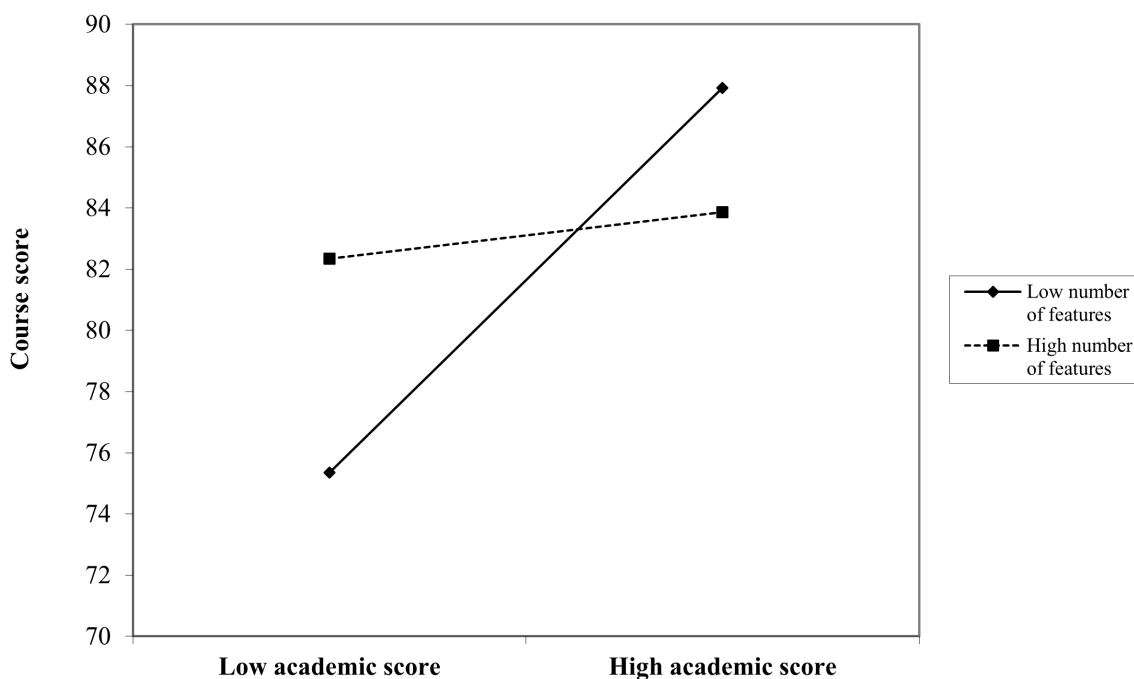


Figure 5

Number of Features as a Moderating Variable of the Relationship Between the Student's Cumulative GPA and the Grade in the Online Course



Discussion

The present study aimed to explore the factors influencing academic performance in online courses, focusing on pedagogical characteristics, demographic variables, and student engagement patterns. Data were collected from 661 students enrolled in 22 online courses across diverse academic disciplines. The analysis incorporated multiple tools, including a detailed coding framework for pedagogical features based on UDL principles and Bloom's taxonomy, as well as metrics for assessing student interaction on the course platform.

The following sections discuss the findings in relation to the study's three main dimensions: pedagogical quality (HOTS), Universal Design for Learning (UDL), and behavioral engagement patterns.

Predictors of Student Success in Online Courses

The results reveal that both demographic and pedagogical characteristics are significant predictors of online course grades, while patterns of student interaction with the course platform did not substantially explain variance. This suggests that the quality of course design and individual student factors play a larger role in academic success than platform activity.

Although the regression models were statistically significant, they explained a modest portion of the variance in students' grades. This suggests that additional factors—such as instructional feedback quality, social interaction, or students' self-regulation—may

further account for differences in performance. Therefore, the findings should be interpreted as indicative rather than definitive, highlighting trends that warrant deeper investigation.

The findings are consistent with previous research indicating that student cumulative GPA is a high indicator of student success in online courses (Cavanaugh & Jacquemin, 2015; Daymont & Blau, 2008; Jost et al., 2012; Vella et al, 2016).

Pedagogical Quality and Higher-Order Thinking (HOTS) Tasks

The study revealed that tasks requiring higher-order thinking skills (HOTS) were associated with lower grades in online courses. This finding aligns with the well-established notion that cognitively demanding tasks pose greater challenges for students, as they require critical analysis, synthesis, and evaluation rather than rote memorization or straightforward application. Although literature often highlights the positive relationship between HOTS and academic success, as shown in Tanujaya et al. (2017), where HOTS significantly predicted higher GPAs among mathematics students, this pattern may not hold uniformly across all disciplines or instructional contexts.

In the current study, the online learning environment may have amplified the challenges of HOTS tasks. Limited real-time support, fewer opportunities for collaborative problem-solving, and potential difficulties in accessing resources could hinder students' ability to perform well on complex tasks. Furthermore, the asynchronous nature of many online courses might reduce the immediacy of feedback that is critical for mastering high-order cognitive skills. This finding suggests that while HOTS tasks are essential for developing critical and creative thinking, their implementation in online courses must be carefully designed with scaffolding and support mechanisms to ensure that all students can engage effectively.

Our results showed that students in online courses with multiple strategies scored significantly lower. The finding that courses with more active learning strategies resulted in lower grades contrasts with prior research emphasizing the benefits of active engagement (Furrer & Skinner, 2003; Gunuc, 2023; Hanaysha et al., 2023; Tay et al., 2021). Several possible explanations can arise in this context. Courses with multiple active strategies might demand higher cognitive and emotional effort, particularly for students in online learning that unaccustomed to such approaches. This could lead to decreased performance. Students might prefer more traditional, structured teaching methods. Courses with multiple strategies could appear chaotic or less coherent. Active learning strategies may not have been implemented effectively. For instance, tasks might not align well with course objectives. Students may perceive the tasks as busywork rather than meaningful engagement.

Universal Design for Learning (UDL) and Student Achievement

The moderating model underscores the differential impact of pedagogical design on students at varying academic levels. For lower-performing students, features such as UDL attributes—diverse presentation methods, multiple expression options, and active engagement practices—were beneficial, likely by reducing barriers to learning and enhancing accessibility. Conversely, for higher-performing students, these features appeared less impactful. Students with higher academic averages may perceive these features as unnecessary or redundant, potentially leading to lower perceived value and engagement. This points to the need for tailored pedagogical strategies that balance accessibility with intellectual challenge to meet the diverse needs of learners in online settings.

These moderation effects highlight an important pedagogical insight: UDL features may serve a compensatory function in online learning environments. Specifically, when the level of UDL implementation is high—meaning the course includes varied ways of

presenting information, diverse modes of student expression, and multiple engagement strategies—the correlation between students’ cumulative GPA and their final course grade becomes weaker. This suggests that UDL-rich environments help lower-performing students improve their outcomes, thereby narrowing the performance gap. In contrast, when UDL features are limited or absent, the correlation between GPA and course grade strengthens, indicating that student success is more tightly tied to prior academic achievement.

The differences in the impact of UDL features on students with varying academic levels have not been previously studied. These differences may stem from distinct needs and the ways in which students at different levels respond to diverse pedagogical approaches. Lower-achieving students may benefit, as prior research suggests, from the broad response to their learning needs (Craig et al., 2024; Izzo, 2012; Yuzlu & Arslan, 2017) and from increased motivation and sense of self-efficacy through tailored learning experiences and a greater sense of control over their learning (Dempsey et al., 2023; Mayes, 2020; Palmer, 2015). In contrast, higher-achieving students may perceive some UDL features as unnecessary or repetitive, potentially leading to frustration or disinterest. These students may prefer more traditional learning methods that allow them to progress rapidly and maximize their potential.

While UDL features are designed to enhance accessibility and flexibility for diverse learners, the findings of this study suggest that they may have unintended consequences for high-performing students. One possible explanation is that such students often prefer efficiency, challenge, and autonomy in their learning. Courses rich in scaffolding, choice, and multimodal content might be perceived by these students as redundant, overly structured, or even distracting. This could result in lower engagement or motivation, especially when the instructional design does not sufficiently differentiate for learners who are already academically self-regulated and cognitively prepared.

From a theoretical perspective, the differential impact of UDL features can be explained through both cognitive and motivational lenses. According to Cognitive Load Theory (Sweller, 1988) and the Expertise Reversal Effect (Kalyuga et al., 2003; Kalyuga, 2007), extensive scaffolding and multimodal guidance that benefit novice learners may become redundant or even distracting for more experienced students, creating extraneous cognitive load. At the same time, self-determination theory (Deci & Ryan, 1985; Ryan & Deci, 2000) suggests that while structured and supportive environments enhance competence and autonomy for lower-achieving students, highly directive designs may restrict autonomy for advanced learners, reducing their intrinsic motivation. Taken together, these perspectives reinforce the need for adaptive course design that differentiates between learner profiles—providing scaffolds and varied representations for struggling students, while offering autonomy and enrichment opportunities for high achievers. For instance, instructors could integrate tiered assignments, optional challenges, or independent inquiry tasks that extend learning without over-structuring it.

Behavioral Indicators of Online Engagement (Login Patterns)

The overall average number of student logins to activities on the course website and average login sequence patterns were not found to predict students’ grades in the online course, nor did they moderate the relationship between students’ cumulative GPA and their online course grades. This finding stands in contrast to the results of Bravo-Agapito et al. (2021), who identified Moodle activity frequency, including logins, forum participation, and interaction with educational materials, as significant predictors of higher academic performance in online learning. Their study suggested that students who engaged more intensively with Moodle achieved higher grades. The discrepancy between these findings

may stem from differences in the types of student interactions measured and the contexts in which the studies were conducted. While Bravo-Agapito et al. (2021) examined a broad range of meaningful interactions, such as active participation in forums and engagement with quizzes, the current study focused primarily on login frequency and sequence patterns, which may not fully capture the depth or quality of student engagement. Additionally, the nature of the course content and the specific design of the online platform could influence how login behaviors translate into academic success. This suggests that the quantity of interaction alone may not be a sufficient indicator of performance; the quality and intent behind those interactions likely play a critical role.

Limitations and Future Directions

This study has several limitations that should be considered when interpreting the findings. First, the research focused on a single institution and a limited number of online courses, which may affect the generalizability of the results to other academic contexts or disciplines. Additionally, the reliance on quantitative measures for coding course characteristics, such as the number of UDL attributes or the cognitive complexity of tasks, might have oversimplified the pedagogical intricacies of the courses. It is important to consider additional pedagogical characterizations that can contribute to the understanding of the researched topic. In addition, it is advisable to conduct interviews or surveys to understand how students at different academic levels perceive the characteristics of the UDL in an online course. Future research should also consider longitudinal designs to examine how pedagogical features and engagement patterns evolve over time and their long-term impact on academic success.

A further limitation is that students were drawn from 22 different online courses, which may introduce some dependency among observations within the same course. Although the current analyses focused on individual-level predictors, future studies employing multilevel models could better account for course-level variance related to subject area, course design, or instructor characteristics.

It should be noted that LMS-based indicators such as login frequency and sequence represent behavioral traces rather than psychological engagement. While they provide valuable insights into students' study patterns and self-regulation strategies, they cannot fully capture motivation, affective involvement, or cognitive investment in learning. Future studies should therefore integrate both behavioral and perceptual data to obtain a more comprehensive understanding of engagement in online learning environments.

Despite these limitations, this study offers several significant strengths and contributions to the field of online education research. First, it integrates two well-established theoretical frameworks—Universal Design for Learning (UDL) and Bloom's taxonomy—to systematically analyze pedagogical features of online courses. This comprehensive approach provides a nuanced understanding of how course design influences student performance and engagement. Second, the study contributes to the growing body of research on online learning by examining the interplay between demographic factors, pedagogical characteristics, and student engagement patterns. By incorporating a moderating model, it highlights the differential impact of UDL attributes on students with varying academic levels, shedding light on the importance of tailoring online learning environments to diverse learner needs. It is important to think about improving the differential support and adjusting the UDL features to fit the needs of students at higher academic levels, for example, through more complex tasks or advanced learning options. Third, the study uses a robust methodological approach, combining detailed coding of pedagogical features with student interaction data from the course platform. This mixed-method approach enhances the reliability of the

findings and provides actionable insights for instructors and course designers. Finally, the study's findings challenge existing assumptions about the universal benefits of higher-order thinking tasks and intensive platform use, offering a fresh perspective on how these factors influence academic outcomes in online learning. These insights can inform the design of more equitable and effective online courses that address both accessibility and intellectual rigor.

Conclusion

This study examined the predictors of academic success in online courses, focusing on pedagogical design, demographic characteristics, and patterns of student engagement. The findings underscore the importance of course design, as both Universal Design for Learning (UDL) features and Bloom's taxonomy levels significantly influenced student performance, while login patterns did not. Notably, tasks requiring higher-order thinking skills were associated with lower grades, suggesting the need for carefully scaffolded support in online environments.

A central contribution of this study lies in identifying the differential effects of UDL features across academic performance levels. While UDL attributes improved outcomes for lower-performing students by reducing barriers to learning, they were less beneficial for high-performing students. This phenomenon may be explained by cognitive load theory and the Expertise Reversal Effect (Kalyuga et al., 2003; Sweller, 1988), as well as self-determination theory (Deci & Ryan, 1985; Ryan & Deci, 2000), which emphasize the importance of autonomy and instructional fit.

These findings highlight the need for adaptive online course design that balances accessibility with intellectual challenge. Instructors should consider offering differentiated pathways that support novice learners while engaging advanced students through enrichment and autonomy. By doing so, online learning environments can promote both equity and academic rigor.

Declarations

Ethical Approval Statement: Data were collected in accordance with ethical standards for the treatment of human subjects. Research ethics approval was obtained by the Institutional Review Board (#3-10/2022).

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Evaluating a Personalized Online Learning Tool for Academic Recovery: Lessons from i-Ready

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Abstract

Many K–12 school districts are leveraging online personalized learning platforms as part of their COVID-19 recovery efforts. We examined the extent to which one such platform, i-Ready, was associated with improved student achievement growth in a southeastern district. We find that students performed better on math and reading standardized assessments when using i-Ready; this is especially true for students who received FRPM, identified as Black, and/or identified as male. Additionally, students whose teachers assigned at least one lesson in addition to automatically assigned lessons benefited even more from i-Ready use. Consistent with prior research, online instructional tools appear most effective when used 40 to 100 hours a school year, with diminishing returns past that point. Our findings suggest that when implemented in a manner that integrates teacher expertise and at an appropriate dosage, platforms such as i-Ready are useful recovery tools that can help school districts enhance student learning, particularly for students belonging to marginalized groups. Further, online learning tools may be particularly beneficial in instances where high cost, low uptake, and/or participant stigma might limit the effectiveness of more traditional remediation strategies.

Keywords: Adaptive learning; blended learning; personalized learning; COVID-19 pandemic recovery; K–12 education policy; quasi-experimental design

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The COVID-19 pandemic resulted in widespread school closures beginning in March 2020 (Goldstein et al., 2020). To maintain schooling during this period, the majority of schools transitioned to crisis-driven virtual learning that continued for many well into the 2020-21 school year (Kaufman & Diliberti, 2021). During this time, students experienced drastic reductions in academic growth compared to pre-COVID-19 cohorts (Darling-Aduana et al., 2022; Kogan & Lavertu, 2021; Kuhfeld & Lewis, 2022; Kuhfeld et al., 2022; Patrick et al., 2021; Pier et al., 2021; Renaissance Learning, 2021). Since then and despite substantial investments in recovery interventions, students have experienced inconsistent academic recovery (Carbonari et al., 2022; Lewis & Kuhfeld, 2023; Curriculum Associates, 2023). Given the challenges to academic recovery, states and school districts continue to seek ways to improve student performance.

Among a host of strategies, many K–12 districts have turned to online tools to assist in student learning recovery. The rapid switch to virtual learning during COVID-19 precipitated large-scale investments in virtual learning infrastructure, programs, and professional development. These investments changed the landscape of how and in what way virtual learning will play a role in students' educational experiences moving forward. As such, our research seeks to assess the effect of one virtual learning strategy—the widely used i-Ready Personalized Instruction platform—on student achievement and recovery.

We studied i-Ready because it was the online learning platform used by the K–12 school district in which we are engaged in a multi-year Research Practice Partnership. As part of their COVID-19 recovery strategy, the school district made i-Ready available to schools. Teachers had discretion over use but were encouraged to assign regular lessons and activities within the platform. Students could access and complete i-Ready activities both during and outside of the school day. i-Ready has several key features typical of online learning platforms, including diagnostic testing, computer adaptive assessment, personalized instruction, and responsive instruction that adjusts pacing based on student understanding. In studying i-Ready, we aim to speak to the potential of the wider array of online learning platforms with similar features.

Studies examining the role of online learning platforms in students' post-pandemic recovery are nearly non-existent. This study is the first that centers solely on online instructional tools. The only other study we are aware of that estimated effect sizes of online learning platforms as a COVID-19 recovery intervention examined them as one of many interventions (Carbonari et al., 2022). As such, researchers were unable to examine the specific features and usage of the various platforms identified. Our study also provides one of the first investigations of online personalized learning platform at-scale. Despite these platforms becoming an increasingly common instructional tool in the post-pandemic education landscape, a recent meta-analysis on the topic failed to identify studies of interventions serving more than 300 students (Zheng et al., 2022).

To extend knowledge in this area, we examined the associations between student achievement growth and i-Ready usage overall, by feature, and for students across various prior performance levels, grades, and sociodemographic variables. We conducted this analysis using data from a K–12 metro district in the southeast. More specifically, we leveraged the staggered rollout of i-Ready in the district as well as detailed administrative and log data from the online

instructional platform. In doing so, this study aims to expand understanding of online interventions and contribute to research on the post-COVID-19 learning landscape.

The Post-Pandemic Education Landscape

Early studies of students' COVID-19 achievement recovery found that the pandemic's negative effect on student achievement grew during the 2020–21 school year (Sass & Goldring, 2021; Kuhfeld et al., 2022). By fall 2021, students began to recover slightly, with students' pace of achievement progress matching or approaching pre-pandemic norms (Kuhfeld & Lewis, 2022; Sass & Goldring, 2022). Fahle et al. (2024) found that students recovered a third of their original loss in math and a quarter of their loss in reading between spring 2022 and spring 2023, reflecting larger than typical growth. Students also achieved improvements in math proficiency on state assessments in most states between 2021 and 2023; however, there is less evidence of recovery in reading (Barnum & Belsha, 2023; Oster, 2023). Despite progress, most students continued to perform below their pre-pandemic national percentile ranking (Carbonari et al., 2022; Curriculum Associates, 2023; Fahle et al., 2024; Sass & Ali, 2022). Kuhfeld and Lewis (2022) estimate that students would need a minimum of three school years to fully recover academically.

COVID-19 Recovery Interventions

Since the pandemic, school districts have offered four main interventions to promote student academic recovery: extended school calendars, tutoring, after-school or out-of-school-time programs, and online instructional tools. Each intervention aims to provide additional instructional and learning time to students beyond the traditional school day. We discuss the implementation and general successes of each in turn.

Extended School Calendars and Days

To offer students additional days of instruction for recovery, some school districts extended their school year (Carbonari et al., 2022). Some districts began the school term early day (Kraft & Novicoff, 2022; Carbonari et al., 2022). Others integrated additional school days or optional days for extra support or teacher professional development, and a third group extended the school day (Kraft & Novicoff, 2022; Carbonari et al., 2022). Pre-pandemic research points to generally positive increases in achievement when students have at least ten more days added to their school calendar (Aucejo & Romano, 2016; Kraft & Novicoff, 2022) or when extending the school day (Kraft & Novicoff, 2022; Figlio et al., 2018; but see Checkoway et al., 2013). Despite this circumstantial pre-pandemic evidence, researchers studying the implementation of extended school time post-pandemic failed to identify positive impacts (Carbonari et al., 2022).

Tutoring

Pre-pandemic research also demonstrates that high-dosage tutoring (of at least 30 minutes daily tutoring outside the school day) can significantly improve student learning in math and reading (Allensworth & Schwartz, 2020; Hashim et al., 2024; Markovitz et al., 2022). Models varied in hours of tutoring (e.g., 30-minute or 90-minute sessions), frequency (e.g., daily or four days a week), and format (e.g., one-on-one tutoring or small group tutoring sessions), yielding

varying levels of effectiveness in student recovery (Allensworth & Schwartz, 2020; Hashim et al., 2024). Districts that offered fewer hours of tutoring experienced limited effects on student recovery, while districts that engaged in more frequent, targeted high-dosage tutoring, traditionally defined as 50 hours or more of tutoring over 36 weeks (see Fryer, 2016), experienced meaningful progress toward recovery (Carbonari et al., 2022).

After-school and Out-of-school Programs

Extended instructional time interventions were also used for pandemic recovery. Strategies to extend instruction time include extended summer school, before-school, after-school, and out-of-school programs. In contrast to extended calendar or school-day interventions, these programs typically offer a combination of academic and enrichment activities, in which students may receive additional instructional time in small groups rather than individualized, high-dosage assistance (Gershenson & Lomax, 2021; Carbonari et al., 2022). These programs tend to target lower-performing students. Pre-pandemic findings suggest that six weeks of summer learning can produce up to a quarter of a year of learning (Augustine et al., 2016). However, the effects of pandemic recovery summer school are minimal, with the most positive study identifying that summer school could close only 2 to 3 percent of a district's total learning losses in math (Callen et al., 2023; Carbonari et al., 2022).

Virtual Learning and Online Instructional Tools

Lastly, districts turned to online instructional tools to aid in student recovery. i-Ready (discussed in more detail below) stands among a host of these platforms (e.g., ALEKS, Dreambox). Some districts rely on online instructional tools during core instruction, while others use them to extend or add instructional time to core instruction (Carbonari et al., 2022). Research on online tool effectiveness as a pandemic recovery strategy is limited. However, Carbonari and colleagues (2022) find marginal effects for this intervention in one district.

Conditional on effectiveness, virtual platforms do not face many of the challenges of other recovery interventions, such as stigma, low uptake, and requiring real-time (synchronous) instructor support. Family and student uptake of educational recovery interventions has been low when delivered as optional programs (Carbonari et al., 2022; Kraft & Falken, 2021; Silver et al., 2022), whereas virtual platforms can be integrated during the school day or assigned as homework. Participation does not require transportation or changes to family schedules. Students can access the program anytime, anywhere using a web browser and their login credentials. Additionally, when integrated within the regular school day, the use of online tools can provide instructional activities for students, allowing teachers to reallocate their attention to higher-impact learning tasks, including providing support for students who require the most remediation (Darling-Aduana & Heinrich, 2018). Lastly, there is some concern that uptake of remediation interventions might be depressed due to concerns over stigma (Kraft & Falken, 2021; Nickow et al., 2024), which is less likely to occur when programs are offered universally. The current study adds to the small, growing body of research on the effectiveness of online tools as a recovery strategy.

Online Instructional Tool Features

According to their website, i-Ready is a suite of online instructional tools that includes assessment, screening, and math and reading lessons. K–8 standards-aligned formative assessments and adaptive assessments provide feedback on specific content students need help mastering. There are also specialized tools designed for students receiving special education services and for students enrolled in pre-kindergarten and Head Start programs. i-Ready marketing materials describe its system as providing “explicit and systematic instruction” within lessons that are “active, supportive, and relevant to their lives” (i-Ready, 2025). Lessons emphasize active strategies like polling, experimentation, learning games, and working with manipulatives (i.e., objects like blocks, dice, and dominoes that can be used to make math more concrete; Carbonneau et al., 2013). Many lessons are also responsive, which i-Ready defines as adjusting the pace of the lesson to how quickly the learner is mastering content. Assessment data is used to direct students to K–8 reading and math lessons covering content they have yet to master. Alternatively, or in addition, teachers can select (or deselect) lessons for their students to complete. Lessons are available in both English and Spanish with features designed to support English language learners. As such, i-Ready combines several features available across online learning tools designed to be blended into traditional in-person instruction, including: vendor-developed, asynchronous content delivery, adaptive online diagnostic assessment, and personalized learning.

Prior research has documented that asynchronous lessons developed by the largest online course vendors tend to focus on lower-order cognitive tasks due to the emphasis on creating highly standardized, structured lessons that can be mass-produced and implemented with minimal instructor oversight (Darling-Aduana, 2021; Darling-Aduana & Hemingway, 2022). Assessments tend to be predominantly multiple-choice questions that only require students to remember and recite instead of thinking critically about content (Darling-Aduana, 2021; Darling-Aduana et al., 2024). In other words, few of these technology-facilitated programs facilitate the type of authentic tasks and interactions that support meaningful online learning (Woo & Reeves, 2008). Additionally, answers to assessments designed by many of the largest online course vendors are readily available online, with frequent evidence of cheating (Heinrich et al., 2019; Darling-Aduana et al., 2024). Consequently, student outcomes tend to be negative, especially for students with lower prior achievement levels or less ability to self-regulate (Heinrich et al., 2019; Ahn & McEachin, 2017; Besecker et al., 2020; Fitzpatrick et al., 2020; Gonzales et al., 2020; Woodworth et al., 2015).

However, instructional quality and subsequent outcomes may be more positive when content is developed by smaller-scale, research-based vendors and/or is targeted toward specific skills (Sahni et al., 2021; Wijekumar et al., 2014, 2017). As an example, Cambolat and Arndt (2024) identified positive learning associations of 0.14 standard deviations among students using Lexia PowerUp, which focuses solely on word recognition for middle and high school students. Students also appear to benefit more from asynchronous, online instruction when blended with traditional, face-to-face instruction instead of as a stand-alone intervention (Heppen et al., 2011; Wiburg et al., 2016).

Beyond delivering course content, one commonly cited but rarely fully realized opportunity to leverage the strengths of technology involves providing students with a personalized learning experience (Enyedy, 2014). The most common digital systems, strategies,

and/or tools used to facilitate personalized learning include adaptive learning or tutoring systems, computer games, robotics, virtual reality, and learner preference-based personalization (Zheng et al., 2022). A meta-analysis identified a moderate association between the use of these technology-facilitated personalized learning tools and student achievement with personalized diagnosis and guidance associated with the highest rate of achievement (Zheng et al., 2022). Studies of ISI-Math and ITSS programs with adaptive learning similar to i-Ready have found positive associations with student test scores (Connor et al., 2018; Wijekumar et al., 2014, 2017).

Prior research on the use of online instructional materials also identified the importance of dosage (i.e., the frequency, number of times, or total time students interact with the tool) (Darling-Aduana & Heinrich, 2018, 2019a; Cambolat & Arndt, 2024; Heinrich et al., 2014). When examining the use of digital tools for out-of-school tutoring across several large metro districts, researchers identified 40 hours of tutoring per school year as a critical threshold for observing positive associations (Heinrich et al., 2014). Similarly, a study examining the use of a computer-assisted literacy program found an hour of use a week (or around 36 hours a year) was necessary for improved test scores (Cambolat & Arndt, 2024).

Importantly, prior research has established that certain students are more likely to benefit from (or struggle with) online learning. Students belonging to advantaged groups, including students with access to technology and internet at home and with higher prior achievement levels, are more likely to be successful learning online (Heinrich et al., 2019; Munoz-Najar et al., 2021; Warschauer & Matuchniak, 2010; Wijekumar et al., 2014). Further, most online learning tools place increased responsibility on students to manage their own learning (Jacob et al., 2016). Consequently, students with stronger self-regulation skills (including older students) or greater parental or teacher-provided monitoring and support are more likely to benefit from online instruction (Darling-Aduana, 2021; Darling-Aduana et al., 2019; Borup et al., 2019; Liao et al., 2021; Picciano & Seaman, 2007).

Additionally, students interact with and experience online learning tools differently based on their sociodemographic background and identities. Several prior studies have found higher rates of engagement with online learning platforms and subsequent achievement among female (versus male) high school students (Darling-Aduana et al., 2022; Lowes et al., 2016; Mann et al., 2021). Students receiving FRPM and from historically marginalized racial groups were notably less likely to achieve expected learning gains when learning online (versus face-to-face) during the pandemic (Darling-Aduana et al., 2022; Mann et al., 2021). It is, of course, possible, given the differential effects of the pandemic, that these associations may be due to confounding factors. In contrast, a recent meta-analysis of 36 studies found that English language learners experienced moderate gains in literacy ($ES = 0.47$) when taught in technology-integrated versus fully face-to-face classrooms (Lee et al., 2022; see also Darling-Aduana & Heinrich, 2018; Cambolat & Arndt, 2024). Results from students receiving special education services who are learning via technology show positive, null, and negative associations with learning observed across three different blended learning environments (Basham et al., 2016; Pace & Mellard, 2016).

Further complicating the matter, the above studies examine a range of online learning contexts, including fully online courses and technology-integrated, traditional (i.e., blended)

classroom environments. Research on adaptive learning programs, like i-Ready, is more limited. One prior study of i-Ready, reviewed by the What Works Clearinghouse, identified positive associations with achievement (Randel et al., 2020). The study was rated Meets WWC Standards with Reservations due to the use of a quasi-experimental (versus experimental) research design (WWC, 2024). i-Ready received a rating of Partially Convincing Evidence on the Academic Intervention Tools Chart (2025) for the same 2020 study by Randel and colleagues. Similarly, Evidence for ESSA awarded i-Ready a Moderate rating based on a single quasi-experimental study that identified positive associations with test scores (Evidence for ESSA, 2025; Holzman & Duncan, 2022). All of the reports reviewed for these ratings were conducted by or on behalf of Curriculum Associates, the vendor that sells i-Ready. Common Sense, a non-profit funded by corporate and foundation sources, also offers generally positive reviews of the tool as a test-prep solution but cautions that it is not a replacement for classroom teaching and that activities follow a similar format that can become repetitive (Common Sense, 2025). Educators have also raised concerns regarding recommendations by the publisher and, in some states, to use i-Ready as much as 90 minutes a week, particularly if i-Ready is used in place of in-person instructional experiences (Gates, 2024; McKinnon, 2018).

When reviewing studies using adaptive learning programs similar to i-Ready, we identified one study that observed positive math test score gains among second-grade students, appearing consistent across poverty level, gender, and prior math test scores (Connor et al., 2018), while Wijekumar and colleagues (2014) found that students with high prior achievement obtained higher gains when using an adaptive, technology-based literacy tool. Perhaps most importantly, the previous findings on online learning have largely been obtained in the context of a “normal” academic year in which students and teachers are not faced with extenuating circumstances that could also influence outcomes. The research on academic recovery is growing; however, most studies do not focus exclusively on the role of technology in meeting recovery goals. Instead, scholars have centered recovery research around tutoring and extended time programs.

Accordingly, this study extends existing research on the efficacy of COVID-19 recovery interventions to online instructional materials by examining the following research questions: (1) To what extent was student use of online instructional materials associated with improved student achievement growth in the post-pandemic era? (2) By how much did student achievement growth vary by i-Ready usage and whether the teacher or automated system assigned instructional materials? (3) To what extent did students experience differential rates of student achievement growth associated with i-Ready usage by prior performance level, grade level, and sociodemographic variables (i.e., gender and race/ethnicity as well as English learner (EL), free and reduced-price meals (FRPM) eligibility, identified disability, and disciplinary status? We detail the setting, sample, data, and analytic strategy employed to answer these research questions in the following section.

Methods

Setting, Sample, and Data

We partnered with a school district in a southeastern metro area that uses the i-Ready Personalized Instruction platform as a COVID-19 recovery strategy. In addition to use during the school day, students could access the platform anytime, anywhere using a web browser and their login credentials. Our research partner is a one-to-one district that provides Chromebooks to all students, with grant funding used to provide internet hotspots to students without internet access. To support this study, the district partner provided access to student-level administrative and log data on i-Ready usage and scores, demographics, summative assessment test scores, and school characteristics.

The i-Ready platform provides interactive lessons and nationally normed adaptive formative assessments. Additionally, the district conducts fall, winter, and spring Measures of Academic Progress (MAP) assessments, allowing for the estimation of achievement growth at the semester level. MAP is a computer-adaptive standardized assessment used by over 16 million students across over 50 thousand schools (NWEA, 2015). We report MAP test scores as z-scores, which we calculated by standardizing scale scores by grade and subject, so that the mean of each test score (by grade and subject) is zero with a standard deviation of one. Standardizing the variables in this manner allowed us to compare across grades and subjects. Z-scores were calculated based on the national distribution of pre-pandemic scale scores.

Of the 131 schools in the district, 81 used i-Ready during SY 2021–22 (Year 1). Eighty-four schools used i-Ready during SY 2022–23 (Year 2). The district prioritized providing low-performing schools access to i-Ready. In Year 1, schools that were currently or previously identified as Comprehensive Support and Improvement (CSI) ($n = 35$) were more likely to use i-Ready than non-CSI schools (67% versus 57%). CSI schools are an official Every Student Succeeds Act (ESSA) distinction assigned to schools requiring additional support. Schools are assigned CSI status if they are in the lowest performing 5% of schools in the state or if a high school's four-year graduation rate is under 68% in a given year. "Horizon school" is a district-assigned status that aligns loosely, but not perfectly, with CSI status. For this analysis, we included binary variables for both whether a school was ever designated as CSI status and whether a school was ever designated as Horizon status as signs of priority status for i-Ready usage. Thirty-three to thirty-five percent of students attending priority schools used i-Ready compared to 14% of students who did not attend a priority school.

Consistent with the focus on providing priority schools with earlier access to i-Ready, a significantly higher percentage of i-Ready users received FRPM (67%) than non-i-Ready users (59%), as shown in Table 1. Additionally, i-Ready users achieved significantly lower fall standardized test z-scores (-0.63 vs. -0.16 in math and -0.50 vs. -0.11 in reading). i-Ready users were also significantly more likely to identify as Black and EL and significantly less likely to identify as White or Hispanic. i-Ready users were also significantly more likely to be in lower or upper elementary compared to middle and high school.

Table 1

Student Characteristics by i-Ready Usage

	Not i-Ready User	i-Ready User
Fall MAP Math Z-Score	-0.16	-0.63*

	(1.18)	(1.11)
Fall MAP Reading Z-Score	-0.11	-0.50*
	(1.23)	(1.12)
Asian	0.07	0.07*
	(0.25)	(0.25)
Black	0.59	0.70*
	(0.49)	(0.46)
White	0.20	0.15*
	(0.40)	(0.36)
Hispanic	0.11	0.05*
	(0.32)	(0.21)
Other Race	0.03	0.04*
	(0.18)	(0.19)
Female	0.49	0.50*
	(0.50)	(0.50)
FRLM	0.59	0.67*
	(0.49)	(0.47)
ELL	0.17	0.19*
	(0.37)	(0.40)
Emotional disability	0.02	0.02*
	(0.15)	(0.12)
Intellectual disability	0.02	0.01*
	(0.14)	(0.11)
Physical disability	0.00	0.00*
	(0.04)	(0.02)
Any disciplinary incidents	0.00	0.04*
	(0.02)	(0.20)
Lower elementary	0.31	0.55*
	(0.46)	(0.50)
Upper elementary	0.16	0.28*
	(0.37)	(0.45)
Middle school	0.24	0.17*
	(0.43)	(0.37)
High school	0.29	0.00*
	(0.45)	(0.01)
Observations	94,240	27,717

Note. * Significant differences between groups at the 0.05 level

Overall, we observed almost 28 thousand cases where students enrolled in i-Ready, which translated into 41 percent of students participating during years when i-Ready was available at their school and grade level. Much of the disparity in participation occurred in middle school grades, where we observed lower rates of usage, indicating teachers might have selectively assigned certain students to use i-Ready instead of universal enrollment. Additionally, some elementary teachers within schools with access to i-Ready appear to have opted not to use the platform.

Despite differential rates of any i-Ready use by school status, students who used i-Ready completed a comparable number of lessons and had similar mean lesson duration and percentage of lessons passed, whether they attended a priority school or not. On average, i-Ready users completed 26 reading and 20 math i-Ready lessons during SY 2021–22. Importantly, 99% of students who were assigned any i-Ready lesson, passed at least five lessons in each subject, indicating that after being assigned to i-Ready, the vast majority of students continued to use the program for the minimum of one instructional week. Each lesson took students, on average, 20 minutes (in reading) to 25 minutes (in math) to complete, with i-Ready users passing approximately 75% of reading lessons and 81% of math lessons begun. Additionally, 16% of reading lessons and 19% of math lessons were teacher-assigned versus i-Ready-assigned. The district provided schools autonomy in how they implemented i-Ready. We were unable to gather data on implementation practices by school, beyond the previously discussed user data collected by the i-Ready platform.

Table 2*i-Ready Usage by School Type During SY 2021–22*

	Ever CSI	Horizon School	Neither	All
Any i-Ready Use	0.33* (0.47)	0.35* (0.48)	0.10 (0.29)	0.14 (0.35)
Number of Reading Lessons	26.46* (24.50)	22.88* (20.42)	25.81 (23.03)	25.83 (23.60)
Mean Reading Lesson Duration	18.41* (10.89)	17.76* (10.90)	21.46 (14.29)	19.51 (13.04)
Reading Lesson Passed (%)	0.74 (0.22)	0.74 (0.22)	0.74 (30.29)	0.75 (0.22)
Reading Lessons Assigned by Teacher (%)	0.16 (0.26)	0.18* (0.29)	0.13 (0.26)	0.16 (0.27)
Number of Math Lessons	16.61* (15.83)	16.93* (17.25)	20.09 (20.25)	19.56 (19.92)
Mean Math Lesson Duration	23.27* (10.44)	23.60* (10.37)	26.37 (14.14)	24.48 (12.13)
Math Lesson Passed (%)	0.80* (0.22)	0.79* (0.22)	0.83* (0.20)	0.81 (0.21)
Math Lessons Assigned by Teacher (%)	0.18 (0.28)	0.20* (0.29)	0.15 (0.27)	0.19 (0.29)
Observations	15,359	15,393	13,123	27,717

Note. * Significant differences between ever CSI or Horizon status and the rest of the sample at the 0.05 level

Analysis

We used OLS regression, school fixed effects, and inverse probability-weighted regression adjustment (IPWRA) models to examine the relationship between any i-Ready usage and achievement test score growth. We also estimated models that added an indicator for

whether any lessons were teacher-assigned, which are manually assigned to students by their teachers, versus automatically assigned lessons based on the adaptive learning platform. We then used dose-response functions to examine differential associations with achievement growth by number of i-Ready lessons. Lastly, we conducted an analysis of heterogeneous associations by running each model limiting the sample to subgroups of interest.

OLS Regression (with Grade and Year Fixed Effects)

To estimate the extent to which student use of online instructional materials was associated with improved student achievement growth in the post-pandemic era, we estimated an OLS regression model comparing student outcomes accounting for i-Ready access using data from SY 2021–22 and SY 2022–23 (eq. 1). Data were limited to kindergarten through ninth grade, since no i-Ready use was observed in tenth through twelfth grades.

$$score_{igt} = B_0 + B_1 iReady_{it} + B_2 days_{it} + B_3 score_{it-1} + X_{it}B + \theta_g + \sigma_t + \varepsilon_{igt} \quad (1)$$

We estimated separate models for math and reading scores. All models control for the number of days between the beginning and end-of-semester test, lagged test scores from tests administered at the beginning of the school year, a vector of individual-level student characteristics (X_{it}), grade fixed effects (θ_g), and year fixed effects (σ_t). Student characteristics include student race/ethnicity and gender as well as FRPM, EL, and identified disability status (separated into emotional, intellectual, or physical disability). We also accounted for whether the student received any disciplinary referrals. All models used robust standard errors clustered at the school level.

Next, given the district policy that provided earlier i-Ready access to some schools over others, we estimated the same model shown in eq. 1 adding school fixed effects (λ_s), as shown in eq. 2.

$$score_{isgt} = B_0 + B_1 iReady_{it} + B_2 days_{it} + B_3 score_{it,n-1} + X_{it}B + \lambda_s + \theta_g + \sigma_t + \varepsilon_{isgt} \quad (2)$$

We estimated eq. 2 twice, once with all cases and once limiting data to cases on common support from the propensity score analysis. Removing cases off common support has the benefit of preventing outliers without viable comparison cases from skewing estimates but reduces sample size and limits generalizability. More information on the proportion of cases removed due to this specification is provided when discussing IPWRA modeling below.

IPWRA Analysis

When implementing the OLS regression model, concerns remain related to treatment and comparison group imbalance, which can introduce bias into estimates. To minimize this concern, we also employed IPWRA to control for the extent to which there were systematic differences in whether a student used i-Ready based on both pre-treatment and fixed characteristics. The principal benefit of IPWRA includes balancing the treatment and comparison groups on a vector of relevant observable variables, which often results in dropping cases off common support that are so extreme that there are no comparable cases.

To implement this approach, we first estimated the likelihood of receiving treatment (i.e., using i-Ready or having a teacher-assigned lesson) using logistic regression conditioned on the vector of baseline school-level covariates (X_{it}) included in eq. 1 (see also Table 3) related to the prior achievement, socio-demographic characteristics, grade, year, and school CSI/Horizon status (see eq. 3; Rosenbaum & Rubin, 1983).

$$\Pr(z_i=1|X_i)=\frac{1}{(1+\exp[-(X\beta)])} \quad (3)$$

Table 3

Predicting Treatment Variables From Matching Covariates

	Treatment Variables			
	Any Math i-Ready	Any Reading i-Ready	Ever Teacher-assigned (Math)	Ever Teacher-assigned (Reading)
Fall Same-Subject MAP	-0.05***	-0.04***	0.05***	0.01
Inst. Days between Tests	0.01***	0.01***	0.02***	0.02***
Race/Ethnicity (Other Baseline)				
- Black	0.12***	0.20***	0.42***	0.42***
- White	-0.61***	-0.59***	-0.87***	-0.96***
- Hispanic	-0.66***	-0.48***	-0.65***	-0.41**
Female	0.04***	0.07***	0.07***	0.07***
Homeless	-0.38***	-0.39***	-0.20*	-0.25**
FRLM	0.13***	0.15***	0.05**	0.06**
Disability	-0.16***	-0.14***	-0.25***	-0.26***
EL	0.40***	0.50***	0.32***	-0.03
Grade (K Baseline)				
- 1	0.11***	0.10***	0.59***	0.73***
- 2	0.21***	0.24***	1.02***	1.19***
- 3	0.27***	0.36***	1.35***	1.42***
- 4	0.21***	0.31***	1.59***	1.36***
- 5	0.13	0.24***	1.43***	1.36***
- 6	-0.42***	-0.32***	-0.55***	0.01
- 7	-0.88***	-0.71***	-0.07	-0.19***
- 8	-1.01***	-0.85***	0.19***	0.33***
- 9	-8.65***	-8.61***	N/A	N/A

Year (2021–22 Baseline)				
- 2022–23	0.21***	0.36***	0.06**	0.31***
Horizon school	1.08***	1.19***	0.88***	1.00***
Ever CSI	1.22***	1.12***	0.58***	0.52***
Number of cases	105,970	96,280	95,809	86,612

Propensity scores were calculated using matching with a 0.01 caliper, no replacement, and limited to cases on common support. This method resulted in an 81–82% reduction in bias when estimating any i-Ready use and a 77–79% reduction in bias when estimating any teacher-assigned i-Ready lessons (see Table 4, Figure 1). Approximately 5% of the analytic sample was dropped when estimating any i-Ready use due to being outside the range of common support. The sample was more balanced when estimating whether a student had any teacher-assigned i-Ready lessons, which resulted in dropping less than 0.01% of cases.

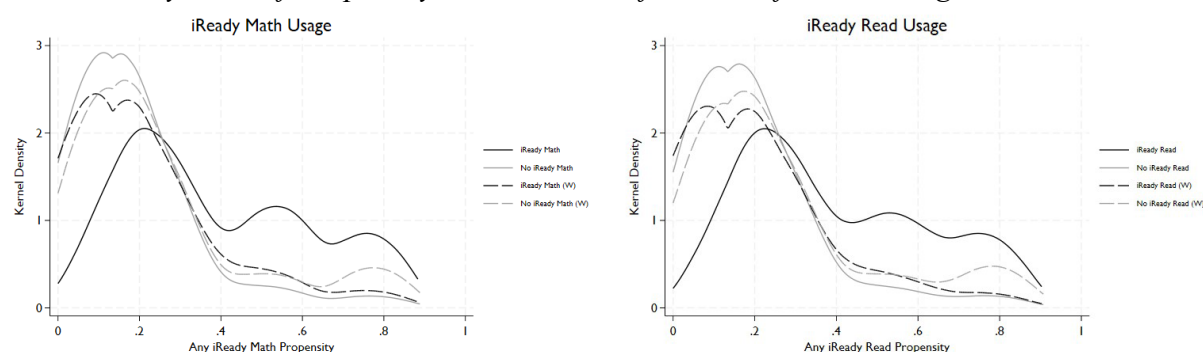
Table 4

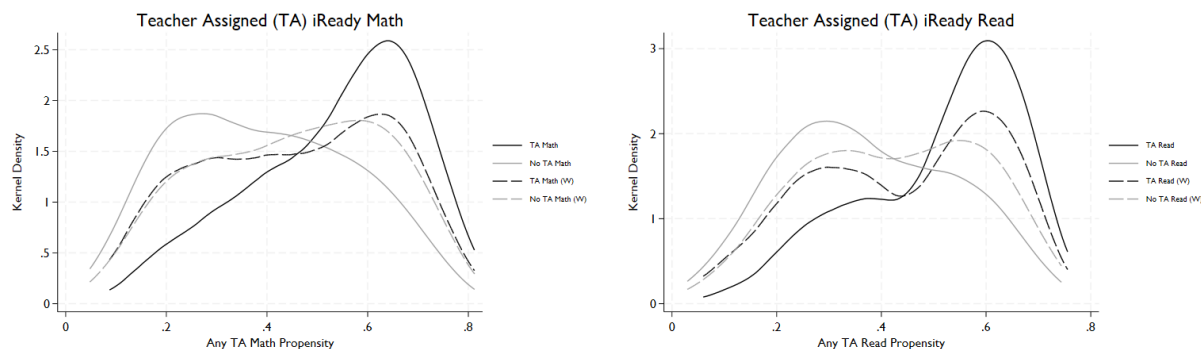
Propensity Score Matching Reduction in the Bias

		Off Support	LR chi2	Mean Bias	% Bias	Variance Ratio
Any Math i-Ready	Unmatched	---	12045.74	27.6	86.3	1.96
	Matched	5,221	512.13	5.2	23.5	1.38
Any Read i-Ready	Unmatched	---	10614.72	27.0	84.0	2.04
	Matched	5,263	418.83	4.9	21.9	1.48
Ever Teacher- assigned (Math)	Unmatched	---	7040.38	23.4	92.9	0.78
	Matched	72	176.26	3.5	18.8	1.08
Ever Teacher- assigned (Read)	Unmatched	---	5761.78	23.6	87.1	0.93
	Matched	2	186.94	3.2	20.3	1.01

Figure 1

Kernel density Plots of Propensity Distribution Before and After Matching





The likelihood ratio chi-squared test results show a substantial decrease in differences between groups on matching variables. The mean bias column reports the difference in means between the treatment and comparison group after accounting for the overall spread of each group. For each treatment variable, the mean bias between groups decreased dramatically. The matched samples had mean bias ranging from 4.7 to 9.7 compared to 16.8 to 27.6 for the unmatched sample. The estimated percent bias remaining in the sample similarly decreased between the unmatched and matched samples. The matched models estimating any i-Ready use (in math and reading) as well as whether the teacher ever assigned a lesson in reading fell below the 25.0 rule of thumb, while the matched model estimating whether the teacher ever assigned a lesson in math was approaching that threshold at 36.5% bias. For well-balanced groups, it is also desirable to have a variance ratio between 0.5 and 2, with a ratio of 1 being ideal to meet the assumptions required for OLS to be the best linear unbiased estimator (Rubin, 2001). The importance of a balanced variance ratio has also been demonstrated using simulated data where the true value was known (Rubin, 2001). The matched models estimating any i-Ready (in math and reading) as well as whether the teacher ever assigned a lesson in math fell within this range. The matched model estimating whether a teacher ever assigned an i-Ready lesson in reading showed a small improvement in the variance ratio but remained below the 0.5 threshold. Lastly, we identified substantial overlap in propensity scores between treatment and control groups visually, with the weighted propensity score distributions contributing to additional improvements in the distribution of propensity scores between groups, which is required to minimize bias (Murnane & Willett, 2011).

After estimating the likelihood of receiving each treatment, we used the resulting propensity score to fit a weighted regression model with covariate adjustment. This model was identical to the OLS regression equation presented in equation one apart from the inclusion of the weights generated from the matching process described above. More specifically, when assigning weights, treatment participants received a weight of $1/(p^*)$, while control participants received a weight of $1/(1-p^*)$ (Imbens & Wooldridge, 2009; Murnane & Willett, 2011). The advantage of this doubly robust method is that the estimates will be unbiased if either the propensity score or regression adjusted models are correctly specified.

To examine our second research question, we estimated separate OLS and IPWRA (eqs. 1–3) that accounted for whether any teacher assigned i-Ready lesson as the treatment in addition to any i-Ready use. If a lesson was not teacher assigned, then the lesson was assigned by the automated i-Ready system.

Dose-response Function

For the second research question, we also estimated dose-response functions to estimate the effect of different doses (or amount of exposure) to i-Ready; this approach is appropriate for use when assignment to treatment is non-random and accommodates continuous treatment measures (Cerulli, 2012). For these functions, we consider the number of i-Ready lessons assigned as the continuous treatment variable. We estimate two functions, one where the dose is zero (eq. 4) and one where the dose is not zero and continuous (eq. 5).

$$w = 0 \rightarrow y_0 = B_0 + B_1 days_{it} + B_2 score_{it,n-1} + X_{it}B + \varepsilon_{it} \quad (4)$$

$$w = 1 \rightarrow y_1 = B_0 + B_1 days_{it} + B_2 score_{it,n-1} + X_{it}B + h(t) + \varepsilon_{it} \quad (5)$$

Equation 5 adds to equation 4 the term $h(t)$, which is a response function that accounts for the dose (i.e., how many i-Ready lessons the student was assigned). We subsequently estimate and graph the resulting non-linear response curves. Given that the modal number of lessons assigned were 20–25 (depending on the subject) with standard deviations of 20–24, we chose to graph only up to 100 lessons to prevent attempts to interpret estimates where there was insufficient data to support robust findings. This choice resulted in dropping no more than 1% of the sample.

As a sensitivity check we generated graphs including these outliers; maximum average treatment effects and trends were comparable whether dropping or including outliers. As with previous analyses, results are associational in nature. We also examined correlations between the number of assigned i-Ready lessons and fall MAP test scores to determine whether students might be systematically assigned more or fewer i-Ready lessons based on their prior achievement level, which could bias the resulting estimates. Among students assigned any i-Ready lessons, we observed no significant correlation between the number of math lessons assigned and students' fall MAP math score ($r = 0.01$, $p = 0.27$). We observed a significant, negative correlation in reading ($r = -0.05$, $p < 0.01$). This translates into being assigned one fewer i-Ready reading lesson for each standard deviation increase in MAP reading test scores. Although significant, this is a low magnitude relationship given that on average, i-Ready users were assigned 20 reading lessons. For this reason, we are less concerned that systematic assignment of i-Ready lessons by prior achievement level might be biasing the resulting estimates.

Heterogeneity Analysis

Lastly, we examined potential heterogeneous treatment effects by estimating eqs. 1–3 limited to each student subgroup of interest (i.e., gender and race/ethnicity as well as EL, FRPM, identified disability, and disciplinary status). We also examined separately students who did not meet state standards on the prior year state level and grade level (lower elementary, upper elementary, middle, and high school). Additionally, we estimated the dose-response function analysis for students with various prior levels of achievement and by FRPM status.

Limitations

Before proceeding to our findings, we reiterate the limitations of our empirical strategy. Findings are based on data from one metro-area district, which has its own unique contextual and demographic factors that may not generalize to all settings. Our analyses are descriptive versus causal as we cannot fully account for endogenous variation. Relatedly, we were unable to fully understand or account for selection into treatment. Among the approximately 67,000 instances where peers in a students' school-grade-year were assigned to use i-Ready, only around 28,000 students were assigned lessons. Given low universality, we estimated models that examined whether the students' school-grade-year had access to i-Ready interacted with whether that student used i-Ready. Estimates for any use of i-Ready remained comparable in directionality, magnitude, and significance, minimizing our concern that not being able to fully account for selection into treatment within school-grade-year bands might be biasing our results.

Importantly, we were unable to collect data on or account for other recovery interventions occurring during the same period that might have been targeting similar schools. And, lastly, we conducted an intent-to-treat (ITT) analysis that examined all students assigned to complete any i-Ready lesson (versus those that actually completed an i-Ready lesson). ITT is an inherently conservative approach and thus may underestimate the true benefit for students who are adequately supported and motivated to fully engage. However, we felt conducting this analysis was appropriate to inform district decision-making. We attempt to provide insight into the possible maximum benefit for students who engage fully with the i-Ready platform by estimating dose-response functions with average treatment effects across the number of i-Ready lessons assigned.

Results

Across all model specifications, we identified a positive association between i-Ready usage and students' math and reading standardized test scores, as shown in Table 5. Estimates from the OLS models with school fixed effects and the IPWRA model were significant and ranged from 0.03 to 0.04 standard deviations higher test scores in reading and 0.04 to 0.05 standard deviations higher test scores in math among students who used i-Ready. Such increases translate into roughly two additional weeks of instructional growth in math and nearly three additional weeks in reading for the median student in our sample (i.e., a 5th grader). Given that the district prioritized providing low-income schools access to i-Ready first, differences in estimates between models that do and do not include school fixed effects may indicate base models were not fully able to parse out potentially deflating confounding influences. Additionally, teacher-assignment of any i-Ready math lessons was associated with 0.02 to 0.04 standard deviations higher test scores, than students who used i-Ready with only computer-assigned lessons. Estimates were larger in magnitude and significant when including school fixed effects and using an IPWRA approach.

Table 5

Associations Between Any i-Ready Usage, Teacher-Assigned Lessons, and MAP Z-Scores

	OLS	School FE	School FE w/ C.S.	IPWRA
Any i-Ready Usage (Math)	0.02	0.04**	0.04**	0.05**

	(0.01)	(0.02)	(0.02)	(0.02)
Observations	103711	103711	98551	98551
Adjusted R-squared	0.827	0.829	0.830	0.839
Any i-Ready Usage (Reading)	0.02	0.03***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.02)
Observations	94534	94534	89334	89334
Adjusted R-squared	0.783	0.786	0.789	0.806
Any Teacher Assigned (Math)	0.03**	0.05***	0.05***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	103711	103711	94393	94393
Adjusted R-squared	0.827	0.830	0.829	0.810
Any Teacher Assigned (Reading)	0.03*	0.04**	0.04***	0.04**
	(0.02)	(0.01)	(0.02)	(0.02)
Observations	94534	94534	85533	85533
Adjusted R-squared	0.784	0.784	0.788	0.771
Student Covariates	Yes	Yes	Yes	Yes
Grade Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
School Fixed Effect	No	Yes	Yes	Yes

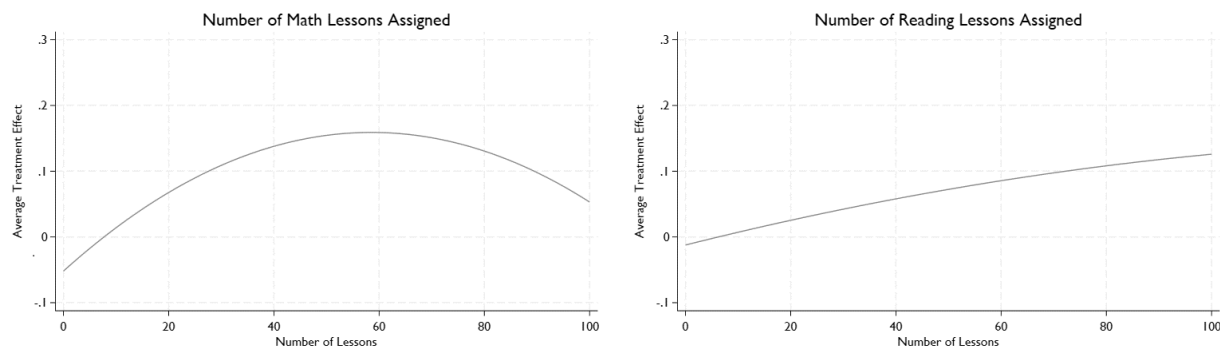
Note. * $p < 0.10$, * $p < 0.05$, * $p < 0.01$

To place these associations in context, we examined i-Ready costs and counterfactuals. Publicly available data suggests that districts pay about \$30 per student annually for a user license. At this rate, we estimate that the district paid roughly \$831,510 (around \$415,000 a year) to serve the sample of students in our study, roughly equivalent to the salary cost of five additional teachers annually. The same district partner also implemented teacher-led “extended learning time” and tutoring models as part of their COVID-19 recovery strategy. These interventions did not yield significant achievement growth for students overall with the exception of struggling middle school students who experienced modest growth when dedicating at least 3 hours per week to academic recovery (Sass, 2024). Thus, in this district’s case and despite the cost, i-Ready was able to successfully support accelerated student achievement growth beyond that observed when studying other recovery interventions.

Next, we estimated dose response functions to examine variations in average treatment effects conditional on the number of lessons assigned, as shown in Figure 2. In math, average treatment effects hit a ceiling of around 0.18 standard deviations, or roughly eight weeks of instructional growth, among students who were assigned 60 or more lessons. By contrast, we identified no ceiling in reading, with average treatment effects continuing to increase in magnitude up to at least 100 assigned lessons. Notably, average treatment effects are never negative in reading, with low magnitude negative associations in math switching to positive once students were assigned at least 10 lessons.

Figure 2

Dose-Response Function for MAP Z-Scores by Number of Lessons Assigned



Lastly, we examined the extent to which there might be differential effects of i-Ready usage, teacher lesson assignment, and the number of i-Ready lessons assigned by subgroup. We report estimates only for the IPWRA model as it is the most rigorous model we can estimate on our full sample. When examining any i-Ready use by subgroup, as shown in Table 6, we continue to identify a significant, positive association with achievement growth comparable to the associations observed across the entire sample for students identified as Black, male, receiving FRPM, and/or with identified intellectual disabilities. Black, male, and students receiving FRPM experienced 2.2 additional weeks of instructional growth in math, and students with intellectual disabilities saw nearly 8 weeks of instructional growth in math using i-Ready. We see similar gains in reading. Black and male students experienced 3.5 weeks of instructional growth; students receiving FRPM yielded 2.8 weeks of instructional growth, and those identified with intellectual disabilities experienced 14 weeks of instructional growth. Additionally, we identified significant, positive associations among female students as well as students in lower elementary grades and/or with prior achievement in the middle third of district test scores in math but not reading. Across all groups and subject specifications, we failed to identify any statistically significant negative associations.

Table 6

Associations Between Any i-Ready Usage and MAP Z-Scores by Subgroup

	Math		Reading	
	N	IPWRA	N	IPWRA
Lowest 3rd prior achievement	39567	0.04 (0.03)	33621	0.03* (0.02)
Middle 3rd prior achievement	33146	0.06*** (0.02)	30440	0.02 (0.02)
Highest 3rd prior achievement	30998	0.01 (0.01)	30473	0.03* (0.02)
Asian	7254	0.03 (0.03)	6554	-0.00 (0.04)
Black	56366	0.05** (0.03)	53423	0.05*** (0.02)
White	11779	0.04 (0.04)	10682	0.05 (0.05)
Hispanic	24724	0.05	20586	0.03

		(0.03)		(0.02)
Other race	4504	-0.02	4071	0.00
		(0.04)		(0.05)
Female	50553	0.03**	46311	0.02
		(0.02)		(0.01)
Male	53158	0.05**	48223	0.05**
		(0.03)		(0.02)
FRPM	60166	0.05**	54623	0.04***
		(0.02)		(0.01)
ELL	23267	0.04	19506	0.02
		(0.04)		(0.02)
Emotional disability	1702	0.14	1549	0.09
		(0.09)		(0.10)
Intellectual disability	1009	0.18**	919	0.20***
		(0.09)		(0.07)
Physical disability	110	1.22	103	0.59
		(0.83)		(0.39)
Any disciplinary incident	5768	0.00	5215	-0.05
		(0.05)		(0.06)
Lower elementary	43050	0.05**	39316	0.02
		(0.02)		(0.02)
Upper elementary	21663	0.03	19440	0.05*
		(0.02)		(0.03)
Middle school	29747	0.02	26779	0.03
		(0.03)		(0.02)

When examining students with any teacher assigned i-Ready lessons by subgroup, we identified significant, positive associations of having any teacher-assigned lessons among students from the lowest-third prior achievement level (in math and reading) and from the middle-third prior achievement level (in math only), as shown in Table 7. Interestingly, we did not identify significant, positive associations among students in the upper-third prior achievement level in either subject when the teacher assigned lessons. Additionally, having any teacher versus solely i-Ready-assigned lessons was associated with significantly higher student achievement growth in both subjects among students identified as male, with disciplinary incidents, and/or in a lower elementary grade across both subjects. Only in math, we also identified positive associations of having any teacher-assigned lessons among students identified as Black, female, receiving FRPM, and/or and in middle school. Only in reading, we also identified positive associations of having any teacher-assigned lessons among students identified as White and upper elementary school.

Table 7

Associations Between Any Teacher Assigned Lessons and MAP Z-Scores by Subgroup

Math		Reading	
N	IPWRA	N	IPWRA

Lowest 3rd achievement	10255	0.08** (0.03)	9433	0.11** (0.04)
Middle 3rd achievement	7894	0.08*** (0.02)	7555	0.02 (0.03)
Highest 3rd achievement	5712	0.01 (0.04)	5808	0.03 (0.04)
Asian	1770	0.10 (0.08)	1535	-0.02 (0.05)
Black	16381	0.08*** (0.02)	15958	0.07* (0.03)
White	1160	0.19 (0.12)	974	0.21** (0.09)
Hispanic	3798	-0.01 (0.06)	3616	0.01 (0.08)
Other race	899	-0.04 (0.06)	841	0.15 (0.09)
Female	11801	0.08*** (0.02)	11397	0.01 (0.04)
Male	12060	0.06*** (0.02)	11399	0.11*** (0.03)
FRPM	15828	0.06*** (0.02)	15355	0.05* (0.03)
ELL	4913	0.07 (0.04)	4655	0.03 (0.06)
Emotional disability	358	0.10 (0.17)	334	0.20 (0.16)
Intellectual disability	278	-0.15 (0.25)	N/A	N/A
Any disciplinary incidents	883	0.12** (0.06)	899	0.20** (0.09)
Lower elementary	13452	0.11** (0.04)	12854	0.10** (0.04)
Upper elementary	7012	0.04 (0.02)	3407	0.10** (0.04)
Middle school	3396	0.04*** (0.01)	6535	0.03 (0.04)

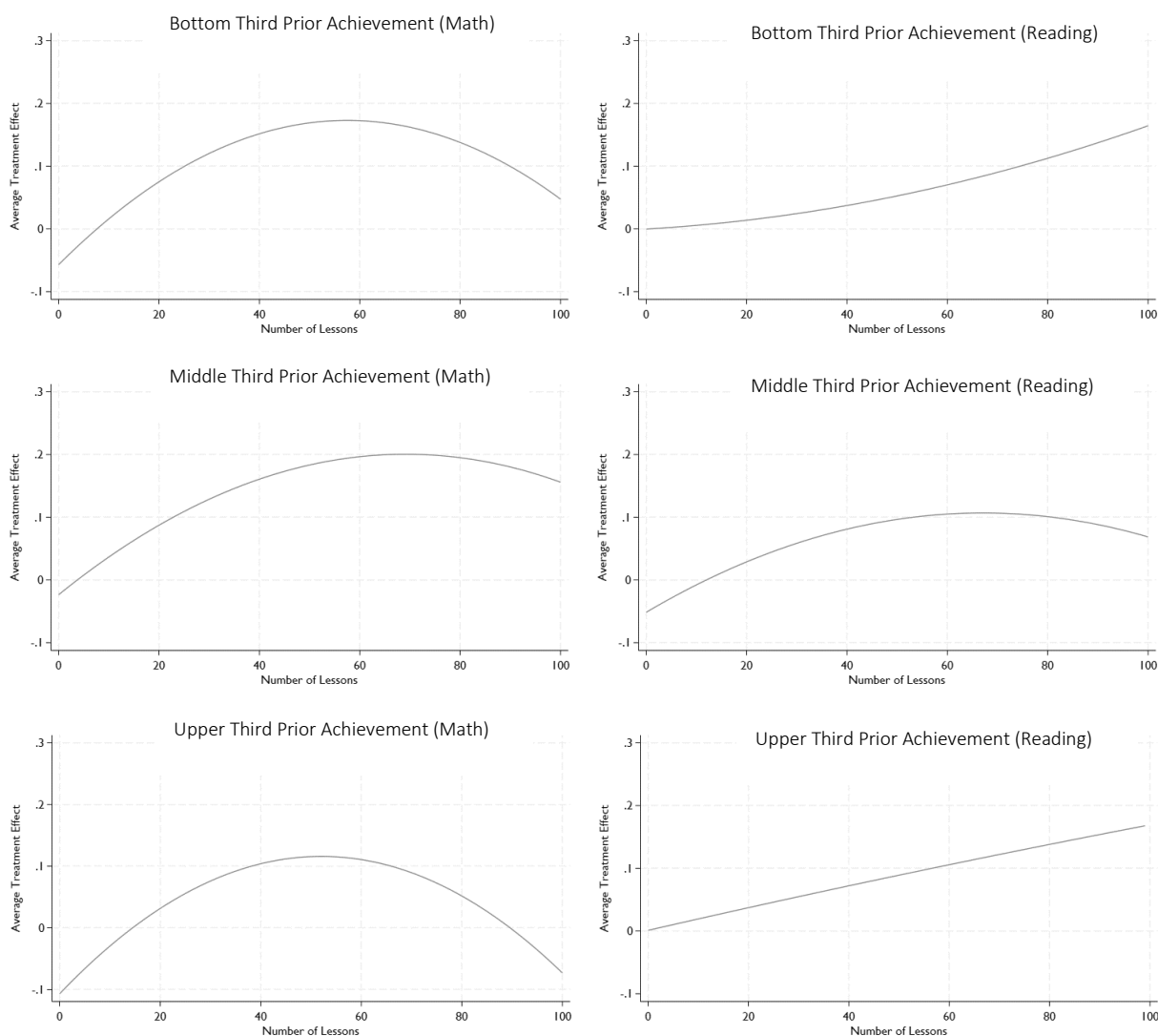
Note. Insufficient data to calculate for students identified as having a physical disability for either subject.
Insufficient data to calculate for students identified as having an intellectual disability for reading.

Additionally, we examined associations between the number of assigned i-Ready lessons and student achievement growth by prior achievement level (in Figure 3) and FRPM status (in Figure 4). Dose-response functions were relatively similar across prior achievement levels in math with maximum treatment effects observed around 50 lessons assigned. However, students in the upper third of prior math achievement experienced the steepest drop in average treatment effects beyond that point, followed by students in the lowest third of prior achievement. Students in the middle third of prior math achievement were least likely to experience negative associations with use across the number of assigned lessons spectrum, the highest maximum treatment effect, and the smallest decline in average treatment effects from that point. In contrast, we observed the opposite pattern in reading with only students in the middle third of reading prior achievement experiencing a ceiling effect (at around 70 assigned lessons). Students in the

lower and upper third of reading prior achievement experienced the largest maximum treatment effects at high intensity use of around 0.2.

Figure 3

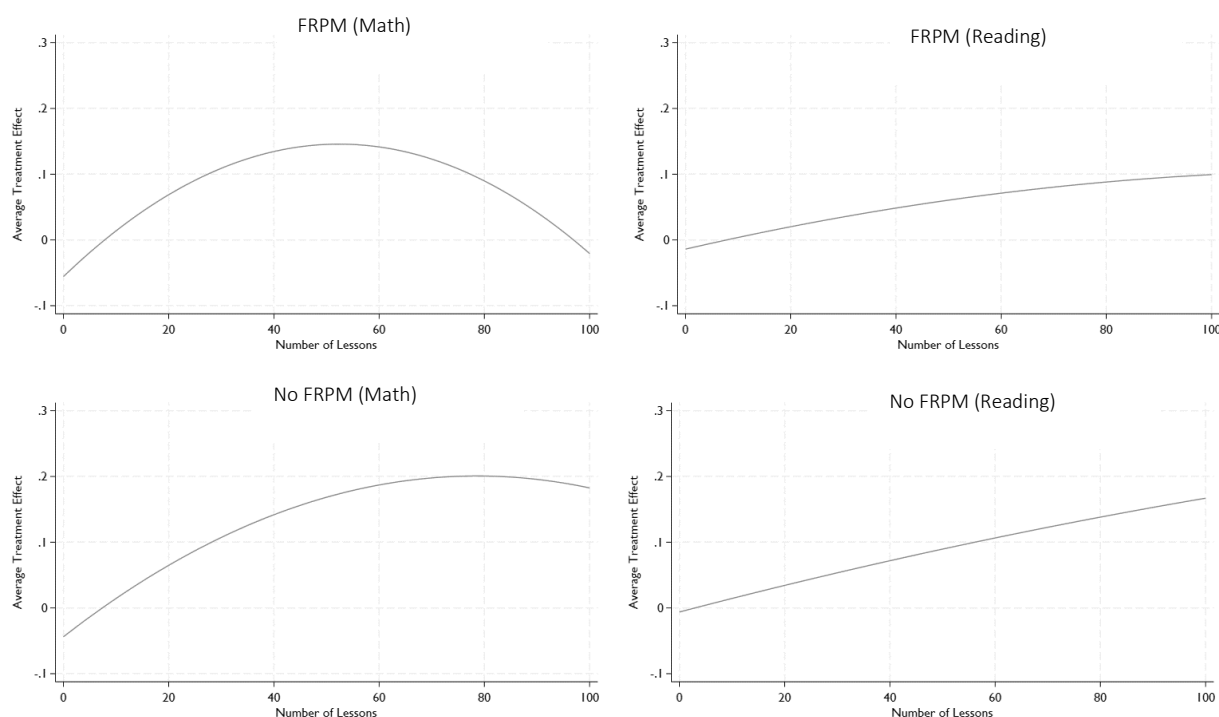
Dose-Response Function for MAP Z-Scores by Prior Achievement



When examining dose-response functions for number of lessons assigned by FRPM status, we identified a ceiling effect (in math) and lower average treatment effects (in reading) among students receiving FRPM. More specifically, the trend between increasing student achievement growth as more i-Ready math lessons were assigned started reversing at around 60 lessons for students receiving FRPM. In reading, the average treatment effect at 100 assigned lessons was only around 75% of the average treatment effect achieved by students not receiving FRPM at that level of use.

Figure 4

Dose-Response Function for MAP Z-Scores by FRPM Status



Discussion

This study provides an impact analysis of i-Ready usage and associations with student achievement growth across different student subgroups and i-Ready content areas. As a widely used virtual learning tool with features similar to other learning platforms on the market, better understanding of platform strengths and limitations can support school district decision-making. Online learning platforms such as i-Ready have the potential to be useful tools to enhance student achievement recovery because they can offer personalized learning that supplements traditional face-to-face instruction. However, empirical research offers mixed findings on their effectiveness, noting various conditions in which they are effective. We discuss the answers to our research questions in turn and provide recommendations for education leaders below.

First, we find that student use of online instructional materials is associated with a 0.04 to 0.05 standard deviation increase in student achievement growth (in our preferred IPWRA models). This translated into roughly two to three additional weeks of instructional growth. The growth observed is particularly important given that i-Ready users in our sample have lower fall standardized test scores in math and reading and are more likely to attend a priority school. The finding conflicts with previous research suggesting negative outcomes for students with lower prior achievement levels (Ahn & McEachin, 2017; Besecker et al., 2020; Fitzpatrick et al., 2020; Gonzales et al., 2020; Heinrich et al., 2019; Woodworth et al., 2015), but aligns with research finding that students perform better on achievement assessments when using adaptive online learning platforms as a supplement (versus replacement) to traditional, face-to-face instruction

(Heppen et al., 2011; Wiburg et al., 2016; Connor et al., 2018). Additionally, we observe larger positive associations among students whose teachers assigned at least one i-Ready lesson in addition to solely using platform-assigned lessons. Students across demographic groups, ability level, and grade level appear to benefit from teacher-assigned online assignments, indicating that teacher input is critical to the effectiveness of online learning platforms.

We find that students experience differential rates of achievement using the i-Ready platform, largely by sociodemographic versus prior achievement or grade-level characteristics. Students who identify as Black, male, FRLM-eligible, or with intellectual disabilities experience more significant improvements using the online learning platform than their peers, gaining up to 14 additional weeks of instructional growth. While these findings do not align with previous research that more advantaged groups are more likely to benefit from online learning, they seem to suggest that i-Ready can assist populations of greater need and of fewer resources. One potential reason why we did not find inequitable outcomes may be the district's investment in one-to-one devices and hotspots for students to mitigate disparities in access. i-Ready users in our sample are more likely to identify as Black, an English Learner, and FRPM-eligible in an elementary grade, so the findings may also reflect the unique demographics of study context. Nevertheless, the gains of students from historically marginalized groups while using i-Ready offers insight into its usefulness in addressing both pandemic-related achievement recovery and historical demographic-related achievement gaps.

Surprisingly, we find only minimal differential achievement related to i-Ready usage based on prior achievement or grade level. Previous research contends that older students with stronger self-regulation skills and those with higher prior achievement levels are more likely to benefit from online learning platforms such as i-Ready (Darling-Aduana et al., 2022; Heinrich et al. 2019; Munoz-Najar et al., 2021; Warschauer & Matuchniak, 2010; Wijekumar et al. 2014), but our study suggests that students of various grade levels can equally benefit from online learning platforms. In fact, our study demonstrates i-Ready's particular usefulness in supporting students in elementary grade levels, as it was largely used in second- through fifth-grade classrooms, and we observe the largest gains (nearly 8 weeks) in math for students in lower elementary grades. The only significant variation observed by prior achievement level is slightly stronger achievement gains in math among students in the middle third prior achievement group.

Finally, the study reveals the achievement limits of adaptive online platforms. Students experience diminishing returns in math after completing around 50 or more lessons (between the fall and winter MAP testing window), apart from students who perform amongst the middle third of the district's math test score distribution. Conversely, students continue to experience gains in reading beyond this point and up to at least 100 assigned lessons, but here students in the middle third of the district's reading test score distribution begin to experience diminishing returns after completing roughly 70 lessons. Similar trends emerge when we observe the dosage effects for FRPM-recipients. Overall, the findings are consistent with previous research on dosage-response functions when using online instructional tools that suggest 40 to 100 hours of usage are key thresholds for positive learning outcomes for students (Heinrich et al., 2014; Darling-Aduana & Heinrich, 2018). However, findings also reveal that expanding beyond the thresholds may not be a wise investment of instructional time or student effort.

The global pandemic forced a rapid shift in learning delivery and expanded the role of virtual learning in students' educational experiences. Online learning platforms such as i-Ready have become a part of schools' and teachers' instructional toolkit to serve students across Grades K–8 and ability levels. Our findings suggest that online learning platforms are valuable tools that school districts should maintain or adopt to aid in COVID-19 achievement recovery. Schools and districts that serve large historically marginalized populations could especially benefit from the investment, as our findings show that the platforms bode well for these students, so long as device and home internet access are ensured.

However, we caution districts against using online platforms as an “auto-pilot” replacement for classroom instruction. Adaptive, personalizing learning is a key feature of the i-Ready system and likely contributes to the achievement gains we observed but extending the adaptive learning beyond threshold points may not benefit students. What's more, students with the lowest and strongest math ability and median reading ability may begin to lose the academic benefits of the platform before their peers, so it's important that schools and districts support teachers in using the online platforms as complementary tools to in-person instruction in which teachers' discretion is used to assign online lessons. Our findings also show that students perform better when teachers monitor frequency of use and assign lessons strategically. Supporting teachers through additional training on how to best assign lessons and the strengths and weaknesses of the platforms could also aid in achievement recovery for students.

Scholars and practitioners alike have been critical of the progress and pace of academic recovery of students post-COVID-19, with some optimistic that students are beginning to meet and exceed their pre-pandemic learning levels. Others are more skeptical, arguing that students will need much more time and support to meet such outcomes. Online adaptive learning platforms such as i-Ready appear well-equipped to support recovery goals, with several logistical advantages over other recovery interventions, which tend to have higher costs and struggle with low uptake and participant stigma.

Declarations

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Ethics Statement

This study was conducted in accordance with recognized ethical standards. The study underwent IRB review at Georgia State University (Approval No. H22434), where it was determined not human subjects research.

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AI Use Statement

The authors did not use generative artificial intelligence (AI) in the preparation of this manuscript.

Conflicts of Interest Statement

The authors declare no conflicts of interest related to the research, authorship, or publication of this article.

Data Availability Statement

The data that support the findings of this study are available from the school district partner. But restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are, however, available from the authors upon reasonable request and with permission of the school district partner.

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Effect of Online and Face-to-Face Engagement and Formative Assessment Score on Flipped Programming Course Outcomes and Satisfaction

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Abstract

In recent years, the flipped classroom model has gained attention for its ability to enhance learning by combining face-to-face (f2f) interactions with online activities. This study explores how different engagement levels—both online and f2f—affect course outcomes and student satisfaction, focusing on programming courses. Using advanced techniques that is, multiple regression and classification and regression tree (CART), the research examines the impact of engagement types on course satisfaction and learning outcomes. Undergraduate level object-oriented programming and database management courses were delivered via a learning management system (LMS) using a flipped instruction model. Engagement data was collected from LMS event logs, and satisfaction was assessed as a usability measure using the System Usability Scale (SUS). Engagement metrics and variables were derived from the raw data for analysis. Regression analysis demonstrated that perceived usability could be predicted by engagement data, accounting for 45% of the variance. Additionally, classification results identified online engagement as the most critical factor influencing student success. The research also highlighted the importance of formative assessment scores and f2f interactions, that is, completing lab assignments, in determining course outcomes. This study underscores the complementary roles of f2f and online activities in flipped classrooms. It provides strategic insights into designing more effective LMS-supported courses by emphasizing the need for balanced engagement strategies. These findings can guide educators in leveraging both engagement types to maximize student satisfaction and success in blended learning environments.

Keywords: Flipped classroom, programming courses, decision tree, hierarchical clustering.

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E-learning is defined as an internet-based instructional method in which content is delivered electronically, either partially or entirely, via web browsers, the Internet, multimedia platforms such as CD-ROMs and DVDs, cloud-based platforms, or dedicated application software (Lew et al., 2019; Riahi, 2015). Frequently supported by learning management systems (LMS), which enable the creation, management, and delivery of course materials worldwide (Turnbull et al., 2022), e-learning has reshaped traditional educational paradigms. The primary challenge for designers and human–computer interaction specialists is to develop tools that effectively engage novice learners and support their distance learning experiences (Ardito et al., 2006). Engagement is widely regarded as a fundamental determinant of learning outcomes, instructional quality, and student satisfaction (Fisher et al., 2018; Lai et al., 2021), and its enhancement is essential across traditional classrooms, e-learning platforms, and LMS-supported flipped classrooms.

Flipped Learning, in particular, has emerged as an effective pedagogical model, defined as the relocation of direct instruction from the group learning space to the individual learning space, while class time is transformed into a dynamic and interactive environment where educators guide students in applying concepts and engaging creatively with the subject matter (Flipped Learning Network, 2014). This approach has proven especially effective in programming education, where problem-solving and practice-based learning are essential (Almassri & Zaharudin, 2023; Karabulut-Ilgu et al., 2018). Although engineering and applied disciplines emphasise problem-solving, theoretical knowledge remains indispensable, and the flipped model has been suggested as an effective means to address theoretical requirements while freeing class time for practical application (Karabulut-Ilgu et al., 2018).

In a flipped classroom (FC) model, students interact with instructional content, commonly through lecture videos, outside of class, while class time is dedicated to hands-on activities and practice. This approach has proven particularly beneficial in programming education, where complex concepts require iterative practice and problem-solving. The FC model promotes self-efficacy, engagement, time management, student-teacher interaction, independent access to course materials, and regulation of learning flow, enabling students to control the pace and sequence of their learning. (Chiu et al., 2023; Mohamed, 2020; Taşpolat et al., 2021). Nevertheless, challenges such as technological demands, low video completion rates, and reduced attendance persist (Taşpolat et al., 2021). In programming education, these challenges are compounded by high cognitive load (Eusoff et al., 2021), differences in learning styles, interests, and motivation (Chen & Hsu, 2022), and varying levels of computational thinking skills (Menzi Çetin, 2025). Limited laboratory hours further exacerbate these issues, underscoring the need for innovative strategies. Numerous studies have confirmed that the FC approach enhances engagement and learning outcomes in programming and computer science courses (Almassri & Zaharudin, 2023; Cassano & Di Blas, 2024; Cheng et al., 2021; Durak, 2020; Özer et al., 2018; Shaarani & Bakar, 2021). Still, low engagement and high dropout rates continue to negatively influence course success (Malkoç et al., 2024), making student engagement a central issue for the effectiveness of FCs (Lai et al., 2021).

Engagement in LMS-delivered flipped classrooms is closely tied to student satisfaction and acceptance. The usability of LMS platforms is a decisive factor in overcoming barriers such as techno-tolerance and low engagement, making intuitive design and interactivity crucial for sustaining participation (Almusharraf, 2024). Engagement, as a key indicator of user behaviour in virtual task-oriented learning environments, is often measured through activity tracking, including downloads, clicks, shares, and task completion

(Morrison & Doherty, 2014; Wiebe et al., 2014). Prior research has established a strong connection between engagement and usability: Lee and Koubek (2010) found that system use significantly influences perceived usability, aesthetics, and user preferences; Harrati et al. (2016) showed that engagement metrics such as task duration and number of clicks play a crucial role in shaping usability perceptions, and Cao et al. (2019) concluded that usability evaluations differ according to the level of user engagement. Within e-learning environments, both usability and engagement directly affect learning performance (Dahleez et al., 2021).

The System Usability Scale (SUS) has been widely adopted as a reliable tool for evaluating the perceived usability of information systems (Brooke, 1996), and it plays a critical role in e-learning research. Effective usability fosters positive human–computer interaction and engagement (O’Brien & Toms, 2010; 2013), while empirical evidence shows that usability influences LMS usage patterns and user satisfaction (Orfanou et al., 2015; Pan et al., 2024). Notably, Orfanou et al. (2015) reported a significant correlation between SUS scores and frequency of LMS use. Some studies have shown that SUS can be integrated with broader models such as the Technology Acceptance Model (TAM) and Task-Technology Fit (TTF). For example, research during the COVID-19 shift to online learning found that perceived satisfaction positively influenced system usability (measured with SUS), supporting a framework that links usability, acceptance, and satisfaction (Chuenyindee et al., 2022). This demonstrates the academic validity of using SUS to assess course satisfaction in LMS contexts. In this regard, machine learning methods offer new opportunities to predict satisfaction based on engagement metrics and to identify LMS-related variables that shape student achievement. The present study therefore aims to examine the interrelationships among satisfaction, engagement, and other process data. The focus is on using machine learning techniques to predict usability and analyse achievement outcomes. In an LMS-based FC for programming courses, factors affecting success and satisfaction were investigated to overcome previously identified difficulties with this model and increase engagement. As engagement is a critical factor in the model’s success, it was addressed multidimensionally in this study. Metrics relating to student participation in online sessions and laboratory hours were analysed to gain a better understanding of programming course outcomes (i.e. pass or fail) and to gain insight into student engagement.

Theoretical Framework

LMS and Data Analytics

Analytics are used to store low-level user actions and log the actual use of applications or systems. LMS log data provides insights into user engagement by recording usage patterns such as login frequency, time spent online, materials accessed, and forum activity (Alshammari, 2024; Kim et al., 2023; Moubayed et al., 2020). Analytical approaches to LMS data leverage supervised and unsupervised machine learning techniques to cluster and predict student behaviours, offering actionable data to refine course design (Dobashi, 2020; Saiz-Manzanares et al., 2021). The analysis of data collected through LMS is used to improve course design and quality (Dobashi, 2020; Zilinskiene, 2022).

In flipped courses, it is critical to identify student engagement metrics that significantly affect course outcomes (Cardello, 2013; Yoo et al., 2022). Metrics such as frequency of access to course materials, submission rates, and forum participation have been found to correlate positively with academic success (Dooley & Makasis, 2020). Studies that have used LMS log data to measure student online activity have reported on metrics such as login frequency, time spent online, the number of lessons read and downloaded, the number

of quizzes and assignments completed, the number of forum topics read and created, the number of views of course components, and the completeness of course materials (Alshammari, 2024; Tan et al., 2021). Repeated interactions with lecture videos and documents enhance comprehension, particularly in challenging subjects such as programming, where dropout rates are often high (Hsueh et al., 2022). This interaction data can reveal the level of student engagement in FCs supported by the LMS.

Student Engagement Level

User engagement can be defined as the quality of the user experience that characterises positive human–computer interaction. Although it is often equated with user satisfaction, the concept extends beyond this (O’Brien & Toms, 2010). The aim of developing interactive systems in many disciplines is to create engaging experiences (O’Brien & Toms, 2010). In online learning environments, engagement is a reliable indicator of learning outcomes, regardless of the type of interaction (Doo & Kim, 2024).

The term “engagement level” refers to the frequency with which an event or action relevant to a user’s interaction experience occurs. For instance, this could refer to a student posting to a forum or submitting an assignment (<https://docs.moodle.org/401/en/Logs>). User engagement level is defined as the frequency of interaction with the environment or materials, as well as the effort invested by the user (Moubayed et al., 2020). Researchers have proposed a number of engagement metrics, including the number of forum posts, content views, a binary indicator of assignment completion, total time spent and LMS visits (Kim et al., 2023; Moubayed et al., 2020). In this study, user engagement was gauged by the number of uploads, downloads, and views of course components.

Using quantitative methodologies to assess user engagement makes it possible to acquire data on user preferences, creating an opportunity to develop enhanced interactive experiences (Rosales et al., 2018). In their study, Rosales et al. (2018) identified several key parameters that could be used to assess engagement levels, including presence, interactivity, control, feedback, creativity and productivity, communication, and adaptation. Carlton et al. (2019) reported on low-level interaction data, including cursor movements and speed, keystrokes, event counts, and application-level data such as button clicks and time spent on an activity. This low-level data can provide insight into user engagement levels within virtual learning environments (Carlton et al., 2019; Ogbuchi, 2022). Existing literature includes studies that use unsupervised algorithms to categorise students according to their level of engagement. Moubayed et al. (2020), for example, identified two clusters based on engagement metric characteristics, namely interaction-related and effort-related. This study aimed to utilise LMS engagement metrics, specifically, the assignment submission rate, number of documents downloaded, number of video views, number of course and feedback views, and number of forum participations to ascertain the level of online engagement by applying unsupervised clustering techniques.

Predicting Academic Success

Predicting student academic success is a prominent area of research in virtual learning environments (Arévalo-Cordovilla & Peña, 2024; Beaulac & Rosenthal, 2019; Dass et al., 2021), as well as in FCs, with the aim of enhancing the efficiency of learning and teaching in programming education contexts (Chiu et al., 2023; Lin, 2019). Tree-based algorithms can be used to predict academic success and student dropout in an online learning environment. Numerous studies have demonstrated the suitability of these algorithms (Adnan et al., 2021; Beaulac & Rosenthal, 2019; Dass et al., 2021; Hawlitschek et al., 2020). To predict the success of incoming students and assess the efficacy of the implemented teaching model, the

factors that influence success in LMS-supported FCs must be identified. Furthermore, using a decision tree to determine the most effective variable for academic achievement can provide valuable insights for the design of LMS-supported FCs.

Classification and regression tree (CART) is a supervised machine learning method designed for classification and regression tasks, which operates by iteratively partitioning the data based on specific parameters (Durak & Bulut, 2024). CART is highly interpretable and robust model for identifying key variables in case of categorical outcomes (Wang et al., 2024). By applying decision tree models, it becomes possible to identify the most influential predictors of student performance, such as login frequency, time spent on instructional videos, engagement in discussion forums, and timely submission of assignments (Alshammari, 2024; Dooley & Makasis, 2020; Tan, et al., 2021). Variable importance analysis not only highlights the relative contribution of these factors but also provides educators with actionable insights to improve instructional design in LMS-supported FCs (Fan et al., 2024). For instance, recognizing that consistent engagement with course materials is a stronger predictor of success than forum participation may guide instructors in prioritizing strategies that foster sustained interaction with core resources. Furthermore, the early detection of at-risk students through these predictive models enables the implementation of timely interventions, thereby enhancing both retention rates and overall academic achievement in programming education. In line with this, Yoo et al. (2022) demonstrated a regularization technique can successfully identify key predictors such as complete viewings of early instructional videos and repeated engagement with challenging content, enabling the detection of potential low performers as early as the first week of instruction. These advanced techniques are all effective in identifying the factors that influence success in programming courses organised in blended learning environments.

The programming course requires students to engage in abstract thinking and demonstrate an in-depth understanding of programming languages. Due to limited class time and the dual demands of learning grammatical programming concepts and completing sample applications, students may struggle to achieve the course's learning objectives (Durak & Bulut, 2024). In light of these challenges, the flipped learning approach is an effective strategy for enhancing the course's effectiveness. Nevertheless, it is vital to pinpoint the factors that indicate success by examining the data gathered via the LMS setting where the FC approach is employed.

Significance of the Study

The prediction of student success in flipped programming courses (FPCs) is a critical research area with significant implications for improving both learning and teaching efficiency. Programming education presents unique challenges, requiring students to develop abstract thinking, algorithmic reasoning, and coding skills within limited timeframes (Almassri & Zaharudin, 2023). The FC model, which shifts traditional instructional content to pre-class activities, has been proposed as a solution by optimizing in-class time for practical exercises and problem-solving (Chen & Hsu, 2022; Jung et al., 2024; Shaarani & Bakar, 2021). However, its success depends on multiple factors, including student engagement, course design, and LMS usability (Eusoff et al., 2021; Kuo & Chang, 2024; Taşpolat et al., 2021).

A central focus of this study is the classification of factors influencing student success in FPCs and the evaluation of teaching model effectiveness. Decision trees are particularly valuable in this context, as they allow for predicting academic success, identifying at-risk

students, and analysing variable importance while providing visual and interpretable outputs (Adnan et al., 2021; Beaulac & Rosenthal, 2019; Dass et al., 2021; Hung et al., 2020; Lee et al., 2015; Villarrasa-Sapiña et al., 2024). These features make them powerful tools for designing actionable and adaptive instructional strategies (Hawlotschek et al., 2020).

Challenges in Programming Education

Programming courses are demanding, requiring mastery of complex grammatical and semantic structures, adaptation of knowledge to new problems, and completion of intricate coding tasks (Almassri & Zaharudin, 2023). Many students struggle to achieve learning objectives within the limited time available (Eusoff et al., 2021; Topalli & Çağıltay, 2018). To address these challenges, instructional strategies that enhance engagement and performance are essential. Online formative assessment has proven effective in laboratory-based programming and engineering courses, improving both programming skills and overall achievement (Cigdem et al., 2024; Veerasamy et al., 2020). Thus, integrating formative assessment into programming instruction represents a key pedagogical approach for fostering sustainable academic success.

Importance of Engagement and LMS Usability

Despite the advantages of the FC model, challenges such as students failing to watch pre-class videos or engage with materials can undermine this model's effectiveness (Kuo & Chang, 2024; Taşpolat et al., 2021). Enhancing course design, improving LMS usability, and promoting active engagement are therefore crucial. Evidence-based strategies include:

Universal Design for Learning (UDL): Providing content in diverse formats (text, audio, video, diagrams) and ensuring accessible navigation (Montes et al., 2024).

Self-Determination Theory: Supporting learner autonomy through options like self-paced modules or alternative assignments (Chiu, 2021).

Active Learning: Embedding interactive quizzes, simulations, and scenario-based tasks with immediate feedback, which significantly boost engagement (Li et al., 2023).

Structured Discussions: Guided prompts and graded forums to promote interaction and feedback (Lowenthal & Dunlap, 2020).

LMS Analytics: Monitoring metrics such as login frequency, time spent online, completed assignments, and forum activity to detect disengaged students and provide timely support (Alshammari, 2024; Olaleye et al., 2023; Tan et al., 2021).

The Moodle LMS employed in the present study supports student–content, student–student and student–teacher interaction through diverse materials, discussion forums, and personalized feedback. Its analytics tools further enable objective assessment of engagement and usability, providing early insights into student performance. In conclusion, this study aims to advance understanding of the factors influencing success in FPCs by integrating predictive analytics, engagement metrics, and course design principles. By identifying key variables, it contributes to the development of adaptive, engaging and effective learning environments tailored to the challenges of programming education.

Prior Work on LMS Analytics

Due to the performance requirements and time constraints in programming courses, Hawlotschek et al. (2020) recommended analysing some process data, i.e. error and success

count in the programming tasks and task delay (the time between start of the exercise and the first-time students logged into the system to work at the task) to predict the dropout rate. They used the J48 decision tree algorithm to predict early and late dropouts. In the prediction of early and late dropouts, task delay was the most significant predictor, followed by error rate in the submission of coding tasks. Hung, et al. (2020) classified LMS interaction data to predict student success in a flipped programming course; they also conducted hierarchical clustering method to reveal behavioural patterns based on the LMS metrics. They predicted the student dropout rate using the decision tree algorithm with an accuracy rate of 0.89 along with logistic regression and random forest. They analysed the LMS data such as assignment submission status, number of clicks, exam and process scores, and forum posts, and clustered students' learning behaviour based on the dimensions of the learning mode questionnaire: active, regular, on-demand, and negative learning. The study revealed that different learning modes had different learning behaviours, i.e. active learners preferred question and answer activities and forums, while regular learners used weekly materials and submitted assignments on time.

Studies show that in similar applications, students' online interaction behaviour is influenced by their previous programming experience and learning preferences. In addition to learner characteristics, the perception of usability or satisfaction with the system is considered in this study as a factor influencing the success of the programming course. Another factor, the result of the formative assessment, shows the learner's performance score in relation to the learning process. Although Cheng, et al. (2021) showed the positive effect of formative assessment in a flipped programming course, there is not enough evidence about FPCs. In this study, tree-based techniques are applied to model the role of the mentioned factors on the programming course outcomes. Thus, it will provide a general overview of the factors related to the applied model.

Aim of the Study

The focus of this study is to create a decision tree model that categorises students based on their course outcomes (i.e., whether they pass or fail the course) and to determine the significant variables affecting these outcomes in a flipped delivery method, particularly regarding online and f2f engagement. Moreover, the study seeks to examine the influence of course design satisfaction on online engagement. Metrics associated with online engagement were analysed using multiple regression analysis, revealing the most predictive metrics in terms of course satisfaction.

The course outcomes of two programming courses, object-oriented programming and database management, were taken as "passed" and "failed" from the relevant course instructor page in the university's student information system and then binary coded as "1" and "0". The courses were delivered using the FC method, and the online sessions of the courses were conducted through Moodle LMS, an open-source e-learning environment. The LMS was also used during the laboratory sessions of the courses, during which students were asked to upload their in-class assignments to the relevant task on the LMS. While LMS log data was used to reveal both online and f2f engagement, course satisfaction was assessed through the System Usability Scale. By analysing the data obtained, answers were sought to the following questions:

- RQ1: How does course design satisfaction relate to online engagement?

- RQ2: What factors are more effective in predicting students' programming course outcomes?

CART enables interpretable prediction of student outcomes through rule-based classification, while variable importance analysis highlights the relative contribution of predictors, together providing both explanatory and predictive insights.

Method

Participants

The study was conducted in the Management Information Systems department at a public university in Turkey, in two compulsory second-year programming courses: Object-Oriented Programming (n = 62) and Database Management (n = 96). A total of 158 students (68 female and 90 male) who were enrolled on the courses participated. Both courses were delivered via a learning management system (LMS) using a flipped instruction model. Following the introductory "Algorithm and Programming" course in the first year, these courses are intensive, combining theoretical knowledge with practical application. The Object-Oriented Programming course covers key concepts such as inheritance, polymorphism and encapsulation, while the Database Management course covers the entity-relationship model and normalisation. In order to meet the learning objectives, students are expected to integrate theoretical principles with practical problem-solving in software development.

Data Collection

Course Delivery and LMS Activities

The Moodle LMS was installed on a remote web server with the objective of facilitating the delivery of online course sessions in an asynchronous manner. Furthermore, the courses were conducted in the computer laboratory during the scheduled f2f class hours. In the online sessions, students were required to view the lecture videos that had been previously created by the course instructor. In addition to the videos, the instructor prepared and uploaded lecture notes and worksheets. In the discussion forum, students were asked to share suggestions for a problem solution and to participate in question and answer (q & a) activities. Formative, process-oriented assessment was utilized to encourage student participation in the courses and deployed through LMS tools both in online and f2f sessions. Formative assessment is a process-oriented method of evaluation that considers assignments, student reflections, q & a sessions, and other observations by teachers regarding the effectiveness of learning (Dixon & Worrell, 2016). In this study, formative assessment scores were extracted from LMS log data and derived from two categories of course assignments: online and f2f. The f2f assignments were administered during laboratory sessions, whereas the online assignments were assigned following the viewing of instructional videos. All submitted tasks were uploaded to the LMS and subsequently evaluated and graded by the course instructor. Along with this score (*formative score*), other engagement data was obtained from the system event logs stored in the server database using Structured Query Language (SQL) queries. Engagement metrics are illustrated in Table 1.

Table 1*Engagement Metrics and Definitions.*

Metric	Definition
Assignment submission	The binary statement of submission status of the assignments
Num. of document downloads (Dd)	The total number of downloaded documents of each student from the LMS server
Num. of video views (Vv)	The total number of times each student has watched the videos in the system
Num. of forum posts (Fp)	Active actions in the discussion forum, i.e., create a topic and write comments under an existing topic.
Num. of course views (Cv)	Total number of visits of each student to the course pages
Num. of feedback views (Fv)	Total number of views of feedback on assignment submissions or forum comments submitted by the course instructor.
Formative assessment score (Formative_score)	Sum of students' process scores from online and lab assignments.
Online engagement level (Online_eng_level)	Student's activity level in online sessions obtained by clustering analysis.
F2f engagement (Lab_assn%)	The percentage of tasks that have been completed during lab sessions.

Course Design Satisfaction

The course design satisfaction was assessed utilising the 10-item System Usability Scale (SUS), a 5-point Likert scale comprising statements that ranged from *strongly disagree* (value 0) to *strongly agree* (value 4). The questionnaire was added to the LMS using a plug-in and administered. The SUS score was calculated using the equation (Equation 1) proposed by Harrati et al. (2016).

$$Perceived\_Usability = 2.5x[\sum_{n=1}^5(S_{2n-1} - 1) + (5 - S_{2n})] \quad (\text{Equation 1})$$

In Equation 1, the variable S represents the rating of the i^{th} item. The SUS score ranges from 0 to 100 points, with a higher score indicating greater user satisfaction. The data underwent pre-processing to guarantee data normalisation and standardisation, and an outlier analysis

was conducted. Following this, the number of observations in the data set was reduced from 158 to 150. To address the issue of missing values, the mean of each attribute was calculated and then imputed with the assistance of pertinent techniques from the Python Scikit-learn library.

Data Analysis

Preprocessing and Engagement Metrics

The system logs indicate whether each student has either completed or not completed the assigned tasks for each course. Pre- and in-class assignments were labelled in the LMS and the percentage of them submitted was calculated separately and labelled as online assignment submission rate (Online assn%) and lab assignment submission rate (Lab_assn%). Based on the online engagement metrics, clustering analysis was used to determine the level of student engagement in the online sessions. These engagement patterns also provide information about the level of student pre-class activity. The interaction amounts for all activities were initially integer values. After missing data analysis, they were converted to decimal values. Python machine learning libraries were used to process and analyse the data. In addition to the data pertaining to engagement, the responses collected via the SUS questionnaire, and the formative assessment scores were also utilised in the analyses.

Online Engagement Level

To reveal online engagement level, K-means clustering was utilized on the online engagement data. K-means is a widely used unsupervised machine learning algorithm that partitions a dataset into k distinct clusters by minimizing intra-cluster variance (MacQueen, 1967). Each cluster is defined by a centroid, which represents the mean of the data points assigned to that cluster. The algorithm iteratively assigns each data point to the nearest centroid based on a predefined distance metric, commonly the Euclidean distance, and updates the centroids by computing the mean of all points in each cluster. This process continues until convergence is achieved, typically when the assignments no longer change or the reduction in the cost function falls below a threshold (Jain, 2010). The objective function minimized by the algorithm is the sum of squared distances between each data point and its associated cluster centroid. Since each engagement metric was coded as it showed the amount of engagement, the outcome of clustering points to the engagement level of students. Cluster centres were calculated with the help of an unsupervised weighting function; the *silhouette index*, so the dataset was not divided into train and test parts, since the training set is not required to (Shutaywi and Kachouie, 2021). The K-means clustering analysis yielded two distinct groups of students, characterised by varying levels of engagement. The clusters obtained according to the values of the metrics are labelled as low and high engagement. Figure 1 illustrates the clustering performance for 2, 3, 4 and 5 clusters:

Figure 1

Silhouette Analysis for 2,3,4 and 5 Clusters.

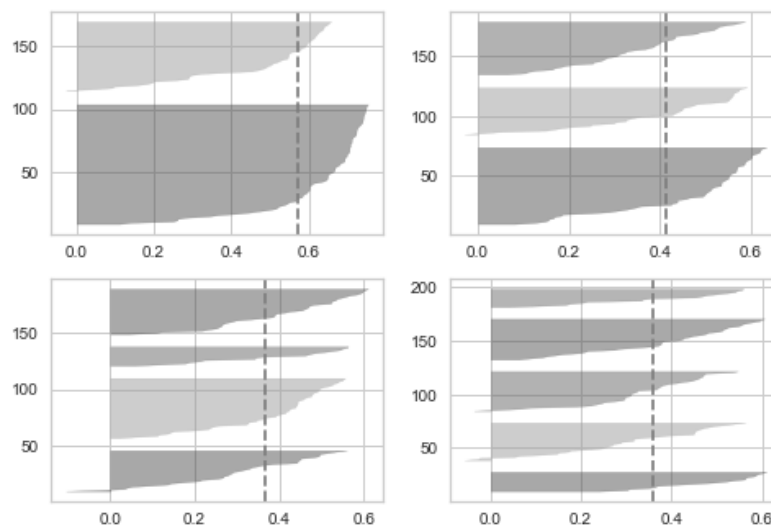


Figure 1 illustrates the Silhouette plots, which are employed for the comparative analysis of cluster centres. The calculated Silhouette coefficients (s_j) were 0.571 which has the highest value for 2 clusters. Table 2 presents the mean value of the centroid means for each metric:

Table 2

Centroid Means for Clusters

Metric	low-level	high-level
Online assn%	50.21	52.86
Dd	2.81	3.32
Vv	4.24	5.46
Fp	8.58	11.27
Cv	46.04	167.32
Fv	7.11	7.94

Multiple Regression Analysis

To examine the relationship between course design satisfaction and online engagement metrics, a multiple linear regression analysis was conducted using Python libraries. The dataset was divided into training and testing sets in an 80:20 ratio. The model included all engagement metrics as predictor variables and perceived usability (SUS score) as the outcome variable. To evaluate the significance of each engagement metric, backward elimination was applied with a threshold of $p > 0.01$ for removal. The final multiple regression model was represented by the Equation 2:

$$\text{Satisfaction} = \text{Intercept} \pm \beta_i(\text{Online\_assn}\%) \pm \beta_i(\text{Dd}) \pm \beta_i(\text{Vv}) \pm \beta_i(\text{Fp}) \pm \beta_i(\text{Cv}) \pm \beta_i(\text{Fv})$$

(Equation 2)

Before proceeding with the analysis, the assumptions for multiple linear regression were tested. To address multicollinearity, the variance inflation factor (VIF) was calculated, yielding a value of 1.946, which is within acceptable limits. Additionally, the Durbin-Watson statistic was computed to assess autocorrelation, and the results confirmed no significant autocorrelation among the predictor variables.

Decision Tree Classification

A classification tree represents a supervised learning problem, wherein the output variable is categorical (e.g. success status) and an associated set of input variables (predictors) is provided. Decision trees are a powerful and readily interpretable classifier, whereby a set of classifiers is constructed using the training data set (Beaulac & Rosenthal, 2019). A classification and regression tree (CART) is a binary tree algorithm, wherein each node has only two child nodes. CART employs the Gini index as a splitting criterion. This implies that the expected error is that of randomly classifying each item according to the probability distribution of class membership within each subset (Lee et al., 2015). The Gini index is calculated using the following formula in Equation 3:

$$\text{Gini}(X_i) = \sum_{y \in Y} p_{iy}(1 - p_{iy}) = 1 - \sum_{y \in Y} p_{iy}^2 \quad (\text{Equation 3})$$

As in the Equation 3, X_i represents the distribution of a variable pertaining to a specific group. Y represents the set of values that the variable in question can assume. In the equation, p_{iy} represents the probability that a sample in group X_i falls into category Y . The Gini coefficient was calculated for each attribute sub-branch, with the result being a division of the nodes into two value ranges, namely “Passed” and “Failed.”

Variable importance analysis: In cases where the predictors exhibit disparate natures, the Gini measure has been observed to overestimate the importance of continuous variables (Storbl et al., 2007). This is particularly pertinent in the context of the dataset under consideration, which encompasses a range of mixed-typed values. Considering this, the recommendation put forth by Beaulac and Rosenthal (2019) is to employ a permutation decrease in importance as a benchmarking input variable. Permutation feature importance is a technique for inspecting non-linear estimators (Breiman, 2001). It involves randomly shuffling the values of a single predictor and observing the resulting decrease in model accuracy. This allows the degree to which the model relies on the predictor in question to be determined. The algorithmic procedure underlying this technique is as follows:

- 1 Construct a tree model DT using training and test data (D)
- 2 Compute the reference score (rs) of the DT on D (accuracy of DT)
- 3 For each feature j (column of D):
 - For each repetition k in $1, \dots, K$:
 - Randomly shuffle column j of D to generate a corrupted version of the data, $\check{D}_{k,j}$
 - Compute the score s_{kj} of DT on $\check{D}_{k,j}$
 - Compute importance i_j for feature ff defined as follow equation:

$$i_j = s - \frac{1}{K} \sum_{k=1}^K s_{k,j} \quad (\text{Equation 4})$$

A permutation decrease in importance was implemented on the existing classifier, utilising the Gini impurity method. The ranking of features was then determined by the provided equation in Equation 4. The results were visualised using Python libraries.

Results

Result of Regression Analysis

The one-way analysis of variance demonstrated that the SUS score exhibited a statistically significant difference in relation to the level of engagement at 0.05 significance level ($F=8.59$; $p=.003$). Considering previous research that suggests SUS is a measure of user perception, and not actual usability (Drew, et al., 2018), highly engaged students found the usability of course design within acceptable limits (Mean SUSs= 68.38), while low-engaged students found it not acceptable (60.49) according to the scale interpretations (McLellan, et al., 2012). On the basis of this finding, it can be assumed that a low level of engagement in online course sessions is associated with a low level of satisfaction with the course design. The results of the multiple regression model with backward elimination method indicated that four of the six attributes with a significance level of less than 0.01 were included in the model: online assignment submission rate, number of video views, number of forum posts, and number of course views. The prediction model indicated that the specified metrics contributed significantly to the model ($F=42.58$, $p<.001$). The results of the prediction model are presented in Table 3.

Table 3

*Regression Model for Prediction of Perceived Usability**

	b	SE b	β^*	RMSE	t	p
Constant	39.89	2.39		0.437		
Online_assn %	0.194	0.046	0.181		4.47	.000
Vv	0.911	0.253	0.632		3.59	.000
Fp	0.407	0.113	0.420		3.59	.000
Cv	0.046	0.013	0.044		3.64	.000

* $R^2=.451$, $Adj.R^2=.428$, $F=19.56$, $p<.001$

Students' online activities other than downloading documents and viewing feedback positively predicted their satisfaction with the system. On the other hand, students with low engagement did not find the system useful. This is an indication that the system has some usability issues from a subjective point of view, which may have an impact on online engagement.

Results of Classification Analysis

The initial decision tree model exhibited an accuracy of 87% and was constituted by a 9-level tree structure. To enhance the model's performance, the cost-complexity pruning process, as proposed for the CART algorithm (Lee et al., 2015), was implemented. The process yielded a confidence coefficient (α) value of 0.0173, which was then provided as a

tuning parameter to the model to achieve the maximum accuracy rate. The newly constructed tree model, comprising four levels and a reduced number of rules, exhibited an enhanced accuracy rate of 89%. Table 4 shows the statistics for the components of the pruned classification tree.

Table 4

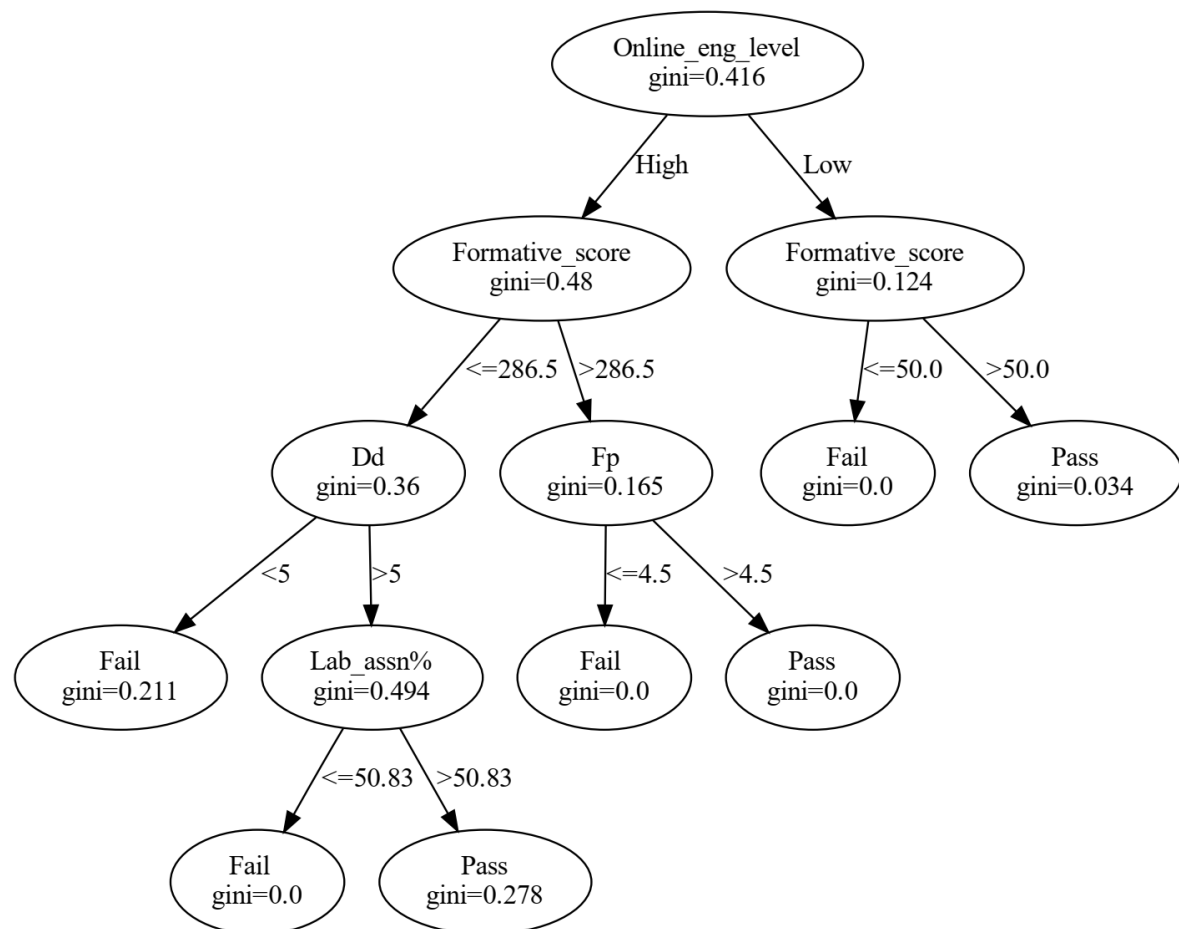
Mean Values of Classifiers for Passed and Failed Students

Metric	Passed (N=105)	Failed (N=45)	Overall (N=150)	p^*
Dd	3.38 (2.9)	2.11 (2.23)	3.0 (2.77)	0.01
Fp	10.38 (8.33)	7.68 (6.51)	9.57 (7.9)	0.055
Lab_assn%	58.94 (22.01)	43.71 (21.32)	54.37 (22.8)	<.001
Formative score	266.45 (125.21)	135.98 (102.78)	227.3 (132.9)	<.001

*Significance level of t-test for compare failed and passed students.

T-test results showed that there were significant differences between the mean scores of passing and failing students in terms of Lab_assn% and Formative_score. In terms of the metrics in question, those who scored above the class average are successful students in the course. The structure of the tree is shown in the Figure 2:

Figure 2 Post-Pruned Decision Tree Model for Course Result Prediction



In the Figure 2, four-level tree illustrated the course success status at leaf nodes, while online engagement level is at the root node. The error matrix and the model performance values for the pruned tree is shown in Table 5:

Table 5

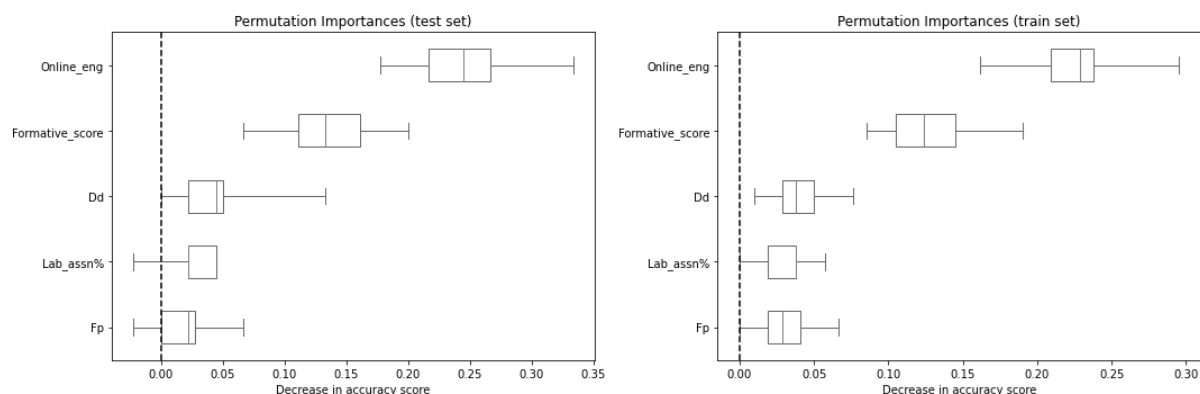
Error Matrix and Model Performance

	Actual 1	Actual 0	Precision
Predicted 1	28	3	0.93
Predicted 0	2	12	0.80
Recall	0.90	0.86	
Accuracy	0.89		

As illustrated in the Table 5, the model was classified according to the input variables based on the course achievement, with an accuracy rate of 89%. Other performance values are F-1 score and Area Under ROC Curve (AUC) are respectively 0.92 and 0.88, the mean squared error of the classification model is 0.11. In terms of variable importance analysis as shown in the Figure 3, online engagement level is the most influential factor on the model accuracy, followed by the formative assessment score, number of document downloads (Dd), laboratory assignment submission rate (Lab_assn%) and number of forum posts (Fp). As a result of the variable importance analysis shown in the Figure 3, the variables (Online_assn%, Vv, Cv, Fv, As_sub_time) that did not have a significant effect on the accuracy of the model were removed from the analysis and the model was reconstructed.

Figure 3

Boxplot for Permutation Decrease Importances on Test and Train Data



A variable importance analysis revealed that the online activity level was the most significant classifier. The following variables were identified as having a notable impact: formative assessment score, number of document downloads, laboratory assignment submission rates and the number of forum posts. Alshammari (2024) reported similar classifiers (average submission rate and average content access) on student interaction at a lower DT model accuracy. However, contrary to the relevant research findings (Adnan et al., 2021; Sáiz-Manzanares et al., 2021), number of feedback views did not demonstrate a substantial effect on model accuracy. The comprehensive decision rules for course success are presented in the Table 6:

Table 6*Decision Tree Rules for Passed and Failed Students*

Node	Rule	Class	N.of cases
5	Online_eng_level=Low and Formative_score $\leq$ 50.0	Fail	3
6	Online_eng_level=Low and Formative_score $>$ 50.0	Pass	57
7	Online_eng_level=High and Formative_score $\leq$ 286.5 and Dd $\leq$ 5	Fail	25
9	Online_eng_level=High and Formative_score $>$ 286.5 and Fp $\leq$ 4.5	Fail	1
10	Online_eng_level=High and Formative_score $>$ 286.5 and Fp $>$ 4.5	Pass	10
11	Online_eng_level=High and Formative_score $\leq$ 286.5 and Dd $>$ 5 and Lab_assn% $\leq$ 50.83	Fail	3
12	Online_eng_level=High and Formative_score $\leq$ 286.5 and Dd $>$ 5 and Lab_assn% $>$ 50.83	Pass	6

The rules extracted from the decision tree provided insights into the implementation of the FPC model. Along with online engagement level, formative assessment scores were an important factor in course outcomes. For students with low online engagement, those who scored above a certain number of points on course assignments (both pre-class and lab) were able to pass the course. In addition to high online engagement, students with above-average process performance, as well as students with a certain level of active participation in the discussion forum and students with a high lab task completion rate ($>$ 50.83) have positive course outcomes.

The overall results of the analysis have led to the formulation of several rules that are conducive to success in the FPC course. These rules include a greater degree of interaction with the course elements and higher level of formative assessment score (process performance) are associated with positive outcomes in the programming courses. Course design satisfaction supports course outcomes as it is highly correlated with online interactions.

Discussion

Based on the results of variance and regression analysis, it can be hypothesized that higher satisfaction levels lead to greater engagement with the system. In response to the first research question, it was found that students' satisfaction with the design of the online course is related to indicators of online engagement. In other words, course design satisfaction is predicted by engagement metrics: assignment submission rate, number of video views, forum posts and course views. In terms of system usability, students who found the system useful interacted more with the course elements mentioned. In the flipped classroom, a significant part of the course content is delivered through videos. The ease of accessing the course videos and using other elements (assignments and discussion forum) on the page is due to the simple and clear design of the system and increases student interaction. These student-content interactions, along with student-student and student-instructor interactions facilitated through discussion forums, were strongly correlated with system satisfaction in similar learning environments (Pham, 2025). Research has consistently shown the positive impact of system satisfaction on engagement in learning environments. For example, Ramaswami et al. (2023) demonstrated that students found the LMS dashboard intuitive and easy to use, contributing

to increased engagement. Moreover, perceived usability has been identified as a critical factor in student adoption, satisfaction, and continued participation in e-learning systems and LMSs (Chu et al., 2020; Chuenyindee et al., 2022; Dutta et al., 2021). It has also been directly linked to improved performance and learning effectiveness in LMSs (Orfanou et al., 2015).

The second research question concluded that the level of online engagement is the most influential factor in programming course outcomes, followed by formative assessment scores, the number of documents downloaded, the rate at which laboratory assignments are submitted, and the number of forum posts. While online engagement remains a critical component of success in flipped learning environments, the present study underscores the significant contribution of face-to-face (f2f) engagement, particularly in the context of completing laboratory assignments. Flipped learning models are designed to foster deeper cognitive engagement with course content (Shen, 2024; Smallhorn, 2017; Talan & Gülseçen, 2019), yet the findings suggest that in-person interactions with laboratory assignments play a notable role in promoting overall academic achievement. Some research findings also support the view that the f2f course format, with its interactive features, remains the preferred option for demanding and compulsory courses (Wladis et al., 2025). These two forms of engagement, online and f2f, address different dimensions of student engagement, and together they create a complementary and mutually reinforcing learning experience. This relationship can be meaningfully interpreted through the lens of the ICAP (Interactive, Constructive, Active, Passive) framework proposed by Chi and Wylie (2014). The ICAP framework posits that learning outcomes improve progressively as student engagement shifts from passive reception to interactive participation. In this context, laboratory activities, which emphasize hands-on practice and motor behaviours, align with *active* engagement, while dialogues, whether conducted in person or through online platforms, embody *interactive* engagement. The integration of these modalities within a flipped learning approach reflects a deliberate alignment with the ICAP model, facilitating deeper learning and higher academic performance through the combination of active and interactive learning strategies.

In terms of feature importance, online activity level emerged as the most critical predictor of course success after formative assessment scores. Formative assessments, which evaluated both laboratory and online assignment submissions, had a significant influence on programming course outcomes. Similarly, Wang (2017) found that formative assessment results strongly impacted achievement in flipped classrooms. Additionally, formative assessments and feedback have been shown to enhance student engagement and satisfaction (Cassano & Di Blas, 2024; Cigdem et al., 2024; Ziegenfuss & Furse, 2021). In this study, short feedback was provided to students, and the number of times they viewed the feedback (Fv) was analysed. While feedback was not directly linked to achievement or satisfaction, it contributed to overall online activity levels. As noted in related studies, formative, process-oriented assessments and remote feedback positively impact programming course success (Adnan et al., 2021; Alshammari, 2024; Veerasamy et al., 2020). Additionally, metrics such as assignment submission rates and the number of downloaded lecture materials were identified as significant predictors in programming education (Alshammari, 2024; Hung et al., 2020).

The number of forum posts and document downloads were found to be the most critical indicators of online and pre-class engagement, respectively. Discussion forums became particularly engaging when teachers actively guided discussions, demonstrating that these platforms support knowledge construction rather than merely social interaction (Xie et al., 2024). Contrary to some studies (Hsueh et al., 2022; Shen, 2024) but aligned with Beatty et

al. (2019), the number of video views was not a significant predictor, while document downloads played a more substantial role in the blended learning model. Laboratory assignment submission rates also significantly influenced programming course outcomes, underscoring the importance of f2f, in-class engagement. While online pre-class engagement, especially assignment submissions, was associated with better programming lab performance (Tran et al., 2024), higher engagement in lab assignments was particularly impactful in this study.

Student engagement is a crucial component of quality higher education, directly linked to academic success, positive educational outcomes, and satisfaction (Fanshawe et al., 2025; Fisher et al., 2018; Martinez-Carrascal et al., 2020; Tan et al., 2021). In programming courses, learning analytics can identify at-risk students in LMS-delivered courses, enabling targeted strategies to improve engagement (Adnan et al., 2021; Lu et al., 2018). While efforts to enhance engagement and achievement in programming courses through flipped learning models have been reported (Shaarani & Bakar, 2021; Durak, 2020), this study underscores the importance of perceived usability as a key factor influencing engagement and success, supported by its proposed variables and analysis approach.

Implications

Programming courses are widely regarded as some of the most challenging in higher education, often associated with the highest dropout rates (Arévalo-Cordovilla & Peña, 2024; Eusoff et al., 2021; Ruiz-de-Miras et al., 2021; Topalli & Çağıltay, 2018; Zhang et al., 2023). Given the tendency for lower success rates in such courses, process-oriented metrics, such as assignment completion rates and formative assessment scores, become critical for evaluating progress. Insights from the implementation of programming courses highlight the need for incorporating abundant practical examples and materials into course design. Additionally, formative assessments, along with fostering student-student and student-instructor interaction via discussion forums, play pivotal roles in the success of programming-focused curricula. Presenting course content and resources in a simple, intuitive manner further enhances the learning experience, creating a more user-friendly environment. These strategies collectively address the challenges of programming courses and support student success.

Limitations and Suggestions

A key limitation of this study is the relatively small sample size, which may affect the performance of the classification model. However, recent studies have shown that decision tree algorithms can perform effectively with similar sample sizes when predicting academic achievement (Hung et al., 2020; Sáiz-Manzanares et al., 2021; Villarrasa-Sapina et al., 2024). Accessing large amounts of real data in e-learning environments becomes difficult if MOOCs are not being studied and there are barriers to implementation. Consequently, the generalisability of results obtained through machine learning analyses is reduced. It may therefore be advisable to increase the volume of data by creating synthetic datasets based on the distribution of real data, thereby improving the predictive accuracy of analyses (Shabnam-Ara et al., 2025).

To improve LMS usability and foster course engagement, additional tools and plugins could be developed. For instance, integrating code editors and integrated development environments (IDEs) directly into the LMS to enable compiling and executing coding tasks within the platform could enhance functionality and support collaborative coding activities. Additionally, a video annotation plugin, as proposed by Cassano et al. (2024), could increase

student engagement, encourage active participation in online sessions, and improve the overall effectiveness of instructional methods. Such innovations could significantly enhance student interaction and engagement (Gallego-Romero et al., 2020).

This study measures usability using the System Usability Scale (SUS), which evaluates user satisfaction with an information system (Brooke, 1996). While SUS is well-suited to assess user satisfaction, other usability measurement techniques focus on different aspects, such as effectiveness and efficiency. Given the critical role of user satisfaction in shaping students' learning outcomes and course evaluations in LMS contexts, as highlighted by Ramos et al. (2021), SUS was considered an appropriate tool for this study. Future research could explore alternative usability assessment methods to provide a more comprehensive evaluation of programming course design.

The scope of this study was limited to programming courses in Turkey, which may restrict how widely the findings can be generalised to other educational contexts. Nevertheless, the challenges addressed in this study, such as student engagement, perceived usability and achievement in LMS-supported flipped classrooms, are not unique to Turkey. Therefore, future research could build on this work by testing the model in diverse cultural and disciplinary contexts to enhance its external validity.

Declarations

Disclosure statement: No potential conflict of interest was reported by the author.

Ethical statement: Permission to collect data from students was approved by the Adana Alparslan Türkeş Science and Technology University Research and Publication Ethics Board (Verification code: 7HBN-VDTP-84GB).

Data availability statement: Data will be made available on reasonable requests.

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The Mediating Effect of Academic Buoyancy on the Causal Chains of Online Learning Readiness, Academic Motivation, and Academic Performance

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Abstract

This study investigated how online learning readiness, academic motivation, and academic buoyancy influence academic performance among high school students in an online learning environment during the 2021–2022 school year. Drawing on a descriptive-correlational design and structural equation modeling, the study explored both direct and indirect relationships among these constructs. Results showed that students demonstrated high levels of readiness, motivation, and buoyancy. Notably, online learning readiness positively influenced both academic buoyancy and academic motivation, while academic buoyancy emerged as a critical mediator—channeling the effects of readiness into increased motivation and improved academic performance. In contrast, motivation alone did not significantly mediate the relationship between readiness and performance. These findings underscore the importance of buoyancy in enabling students to convert their preparedness for online learning into tangible academic success. The study highlights the need for educational interventions that not only enhance technical readiness but also build students’ capacity to adapt, persist, and recover from academic challenges in an online learning environment.

Keywords: Online learning readiness, academic motivation, academic buoyancy, academic performance

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Introduction

Educational institutions worldwide, including the Philippines, have experienced a shift in learning modalities in recent years. Online learning, which complements or replaces in-person classes, offers benefits such as flexibility, convenience, and more opportunities for collaboration. However, high-aptitude Science, Technology, Engineering, and Mathematics (STEM) learners who lack the skills and resilience required for remote instruction have exhibited declining motivation, poor coping with everyday academic setbacks, and lower grades. This study, therefore, examines how students' preparedness for online learning, their academic buoyancy, and their motivation influences academic performance in an online learning environment.

Online learning—also called digital, virtual, or web-based learning—delivers instruction and content primarily via the internet, whether synchronously or asynchronously, and in hybrid or fully remote formats. This distinction matters because students' readiness and resilience needs may vary depending on whether they engage in hybrid or fully remote formats (Barbour et al., 2011; Morrison, 2003; Peña-Bandalaria, 2009; Sadiku et al., 2018; Stauffer, 2020; Tsai & Machado, 2002).

In 2020, the COVID-19 pandemic disrupted education globally. In response, schools in the Philippines adopted various learning delivery modes, such as modular, online, blended, and radio/TV-based learning (Republic of the Philippines Department of Education, 2020). The Philippine Science High School (PSHS), which serves high-aptitude STEM scholars, transitioned to blended learning, combining modular and online classes in the curriculum under remote or blended learning beginning in the 2020–2021 school year.

This sudden shift posed challenges for many students. Some experienced difficulties in submitting requirements, earning satisfactory grades, staying motivated, and managing their mental well-being. While distance learning offers flexibility and convenience, it also requires strong motivation, self-discipline, and independent study habits (Mirkholikova, 2020; Simpson, 2013). Limited social interaction, poor internet access, and a lack of proper tools have added to the difficulties faced by learners (Barbour et al., 2011; Chung et al., 2020).

The shift to online learning has made it more important than ever for students to have the cognitive, emotional, and behavioral skills needed to succeed in less structured settings. Online learning readiness (OLR) includes computer/internet self-efficacy, learner control, motivation for online learning, online communication self-efficacy, self-directed learning, self-efficacy, and digital engagement (Chung et al., 2020; Demir Kaymak & Horzum, 2013; Doe et al., 2017; Hung et al., 2010), all crucial in online classes. However, readiness alone may be insufficient. Academic buoyancy, or the ability to deal with day-to-day academic challenges, plays a key role in keeping students engaged. Academic buoyancy predictors, as observed in various studies, include self-efficacy, certain control, academic engagement, academic anxiety, and teacher-student relationship (Einy et al., 2019; Martin & Marsh, 2008; Sadeghi & Khalili Geshnigani, 2016). Buoyant learners are more likely to maintain motivation, which can lead to better academic performance (Barnett, 2012; Colmar et al., 2019; Collie et al., 2015; Datu & Yang, 2019; Datu & Yuen, 2018; Putwain & Daly, 2013).

This study aims to examine how OLR, academic buoyancy, and academic motivation interact to influence academic performance among high-aptitude STEM students in a Philippine STEM high school by modeling the direct and indirect effects of OLR with buoyancy and motivation as mediating variables. While previous structural equation modeling (SEM) studies have linked OLR to motivation and performance (Horzum et al., 2015; Saeid & Eslaminejad, 2017), this is the first to integrate academic buoyancy as a mediator within a Philippine STEM high school context, offering a more comprehensive understanding of student success in online and blended learning environments.

Review of Related Literature

Online Learning Readiness

Online learning readiness (OLR) encompasses the cognitive, technical, and self-regulatory competencies that enable students to succeed in internet-based courses (Hung et al., 2010; Chung et al., 2020). Empirical evidence indicates that higher OLR predicts greater course satisfaction and performance: for example, computer/internet self-efficacy and motivation for online learning positively influence online discussion performance and overall satisfaction (Wei & Chou, 2020), while self-directed learning is one of the strongest predictors of achievement in online settings (Çiğdem & Öztürk, 2016). Furthermore, increased OLR has enhanced academic motivation (Horzum et al., 2015) and supports adaptive learning strategies when students have adequate technology access and guidance (Yasin et al., 2020).

Academic Motivation and Self-Determination Theory

Academic motivation refers to the processes that energize and direct students' learning behaviors. Rooted in Self-Determination Theory (SDT) (Deci & Ryan, 2004), motivation ranges from amotivation through extrinsic regulation to intrinsic regulation, with fulfillment of the basic psychological needs for competence, autonomy, and relatedness fostering more self-determined forms of motivation. In online contexts, students who feel competent (through computer/internet self-efficacy and self-directed learning), autonomous (through learner control and motivation for online learning), and connected (through online communication self-efficacy and teacher–student relationships) are more likely to develop intrinsic motivation, which in turn is linked to higher persistence and achievement (Datu, 2017; Usán et al., 2019).

While SDT posits that fulfilling competence, autonomy, and relatedness needs enhances intrinsic motivation (Deci & Ryan, 2004), few studies have tested whether motivation mediates the translation of readiness into performance.

Academic Buoyancy

Academic buoyancy is defined as students' capacity to successfully manage everyday academic setbacks—such as low grades, conflicting deadlines, and test anxiety—distinct from resilience, which addresses more severe adversities (Martin & Marsh, 2008; Martin et al., 2010). Key antecedents of buoyancy include self-efficacy, academic engagement, self-regulation, and supportive teacher–student relationships (Martin et al., 2010; Yun et al., 2018). Research shows that buoyant students maintain motivation and perform better academically under routine stressors (Colmar et al., 2019; Datu & Yuen, 2018), and that buoyancy can mediate the effects of other constructs—such as self-regulation and motivation—on performance (Datu & Yang, 2019; Putwain & Daly, 2013).

Academic buoyancy has been linked to improved performance under routine stressors (Datu & Yuen, 2018), but its role as a mediator between readiness and motivation—or between readiness and performance—has not been tested in a single integrated model.

Although OLR, academic motivation, and academic buoyancy each predict academic performance in online learning, few studies have examined their joint and mediating relationships—especially among STEM high school students in the Philippines. Past models have linked readiness to motivation (Horzum et al., 2015) and buoyancy to performance (Yun et al., 2018), but none have simultaneously tested whether academic buoyancy and motivation mediate the pathways from OLR to performance. High-aptitude STEM students may experience unique demands in blended environments, underscoring the need for an integrated model in this context.

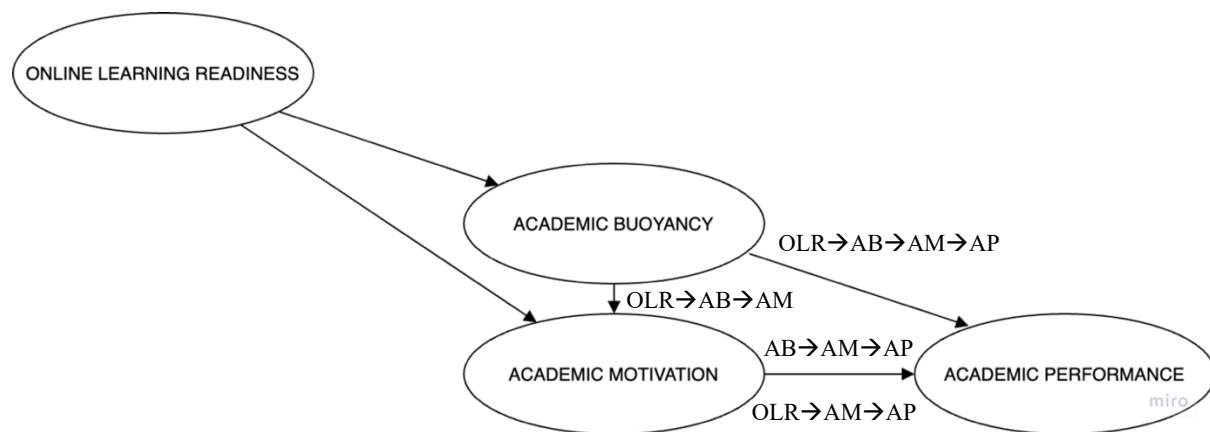
This study is grounded in SDT, which posits that fulfilling competence, autonomy, and relatedness needs enhances students' intrinsic motivation (Deci & Ryan, 2004; Martela & Riekk, 2018). This suggests that OLR provides the control beliefs and perceived competence necessary for academic buoyancy and motivation, which in turn drive academic performance.

Conceptual Framework

Figure 1 illustrates the hypothesized relationships among the study's constructs. Online learning readiness is assumed to have direct effects on academic buoyancy, academic motivation, and academic performance. Academic buoyancy is hypothesized to mediate the relationship between OLR and both motivation and performance, while academic motivation is hypothesized to mediate the relationship between buoyancy and performance, as well as between OLR and performance directly.

Figure 1

Conceptual Framework of the Mediating Roles of Academic Buoyancy and Academic Motivation in the Relationship Between Online Learning Readiness and Academic Performance



Building on these theoretical and empirical foundations, this study addresses the following questions:

1. To what extent does online learning readiness predict academic buoyancy, academic motivation, and academic performance?

2. Does academic buoyancy mediate the relationship between online learning readiness and academic motivation?
3. Does academic buoyancy mediate the relationship between online learning readiness and academic performance?
4. Does academic motivation mediate the relationship between academic buoyancy and academic performance?
5. Does academic motivation mediate the relationship between online learning readiness and academic performance?

Assumptions

1. Online learning readiness will significantly predict academic buoyancy, academic motivation, and academic performance.
2. Academic buoyancy will mediate the relationship between online learning readiness and academic motivation.
3. Academic buoyancy will mediate the relationship between online learning readiness and academic performance.
4. Academic motivation will mediate the relationship between academic buoyancy and academic performance.
5. Academic motivation will mediate the relationship between online learning readiness and academic performance.

Methods

Research Design

This study employed a quantitative research design using multivariate statistical analysis to examine the structural relationships among observed and latent variables in the context of online learning. Specifically, structural equation modeling (SEM) was used to assess both measurement validity and hypothesized relationships while accounting for measurement error. SEM is a robust analytic technique that allows for the simultaneous testing of direct and indirect effects among multiple constructs, providing deeper insights into underlying theoretical frameworks (Da Costa, 2018; Mohamad et al., 2019).

The SEM consists of two main components: confirmatory factor analysis (CFA) to validate the measurement models, and path analysis to test mediating relationships among latent variables. The approach was particularly suited for this study given its focus on testing sequential mediation and its use of validated latent constructs drawn from the Online Learning Readiness Scale (OLRS), Academic Motivation Scale (AMS), and Academic Buoyancy Scale (ABS). These instruments represent theoretically distinct domains aligned with the study's conceptual framework, and SEM's latent-variable approach minimizes measurement error across these scales (Byrne, 2013).

Participants

Participants were 489 science high school students enrolled during the 2021–2022 academic year. Given the small population size and the importance of including all relevant students, total population sampling was employed. Admission to the school is based on performance in a national competitive examination or a predicted score under special conditions, such as calamities or pandemics. The curriculum is structured into three levels: Foundation Years

(Grades 7–8), Advancement Years (Grades 9–10), and Specialization Years (Grades 11–12), with a strong emphasis on science, technology, engineering, and mathematics (STEM) education. Although the grade levels differ in age and curricular focus, data were pooled across Grades 7–12 to maximize statistical power. Table 1 presents the demographic breakdown of participants by grade level and sex.

Table 1

Demographic Profile of Respondents (N = 489)

Respondents	Male	%	Female	%	Total	%
Grade 7	48	9.8%	65	13.3%	113	23.1%
Grade 8	54	11.0%	40	8.2%	94	19.2%
Grade 9	58	11.9%	41	8.4%	99	20.2%
Grade 10	37	7.6%	30	6.1%	67	13.7%
Grade 11	30	6.1%	29	5.9%	59	12.1%
Grade 12	31	6.3%	26	5.3%	57	11.7%
Total	258	52.8%	231	47.2	489	100.0%

Instruments

Three validated self-report instruments were used to measure the study's key constructs: the Online Learning Readiness Scale (OLRS) is an 18-item instrument with five subscales. Items are rated on a 5-point Likert scale. Reported reliability coefficients ranged from $\alpha = .727$ to $.871$ (Hung et al., 2010). The Academic Motivation Scale (AMS) measures intrinsic motivation, extrinsic motivation, and amotivation on a 5-point Likert scale. Internal consistency for the full scale was $\alpha = .81$, with subscale alphas ranging from $.70$ to $.86$ (Vallerand et al., 1993). The Academic Buoyancy Scale consists of four subscales, with items rated on a 5-point Likert scale. Reliability coefficients for these subscales ranged from $\alpha = .748$ to $.923$ (Yun et al., 2018).

Measurement Model Validation

Given that the OLRS, AMS, and ABS instruments have well-established factor structures, exploratory factor analysis was deemed unnecessary. Following best practices for confirmatory measurement modeling (Brown, 2015), confirmatory factor analysis was conducted using the full sample ($N = 489$) to validate the factor structure of each instrument.

Model fit was assessed using multiple indices: chi-square to degrees of freedom ratio (χ^2/df), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR), following the two-index presentation strategy (Hu & Bentler, 1999). Acceptable fit was defined as $\chi^2/df < 3.00$, $RMSEA < .08$, and $SRMR < .08$ (Awang, 2015). All factor loadings exceeded $.50$ ($p < .001$), confirming construct validity. Table 2 shows model fit indices for both the initial and modified models.

Table 2*Model Fit Indices for Confirmatory Factor Analysis*

Model	χ^2	df	p	$\frac{\chi^2}{df}$ < 3	SRMR < .08 ^a	RMSEA < .08 ^a	RMSEA 90% CI		RMSEA p
							Lower	Upper	
Initial	5785	2128	<.001	2.71	.799	.059	.057	.061	<.001
Modified	3444	1510	<.001	2.28	.062	.051	.049	.053	0.194

Note. ^a indicates the range of acceptable levels of fit

Although the χ^2 test remained statistically significant—an expected outcome in large samples—it is well documented that χ^2 tends to over-reject well-fitting models under such conditions (Kline, 2015). Thus, greater interpretive weight was placed on χ^2/df , RMSEA, and SRMR, all of which indicated acceptable model fit.

Reliability and Validity

To evaluate the constructs' reliability and validity, composite reliability (CR) and average variance extracted (AVE) were calculated. CR values of ≥ 0.70 and AVE values of ≥ 0.50 were considered acceptable indicators of construct reliability and convergent validity. Discriminant validity was established by confirming that the square root of each construct's AVE (shown as diagonal elements in parentheses) exceeded its inter-construct correlations (off-diagonal elements). Tables 3 to 5 present these values for the OLRs, ABS, and AMS, respectively.

Although the chi-square (χ^2) test was statistically significant—expected due to the large sample size and number of estimated parameters—this is a known limitation in SEM (Kline, 2015; Marsh et al., 1996). Therefore, model fit was primarily assessed using alternative indices: $\chi^2/df = 2.28$, RMSEA = .051 (90% CI [.049–.053]), and SRMR = .062, all of which fall within the recommended thresholds for acceptable model fit (Awang, 2015; Hu & Bentler, 1999).

Table 3*Reliability and Discriminant Validity for the Online Learning Readiness Scale (N = 489)*

Sub-construct	Items	CR	AVE	CIS	SDL	OCS
CIS	3	.876	.702	(.838)		
SDL	8	.922	.529	.452	(.727)	
OCS	3	.800	.573	.423	.590	(.757)

Note. CR = composite reliability; AVE = average variance extracted. Diagonal values (in parentheses) are the square roots of the AVE; off-diagonal values are inter-construct correlations.

Table 3 summarizes the psychometric properties of the OLRs. Its CR values for its sub-constructs range from .800 to .922, while all AVEs exceed .50, indicating good construct reliability and convergent validity. The square root of the AVE for each sub-construct also exceeds its intercorrelations, supporting discriminant validity. Overall, the measurement model demonstrates acceptable reliability and validity for assessing students' OLR.

Table 4*Reliability and Discriminant Validity for the Academic Buoyancy Scale (N = 489)*

Sub-construct	Items	CR	AVE	SE	CC	AE	TSR
SE	4	.868	.623	(.790)			
CC	5	.880	.596	.659	(.772)		
AE	4	.812	.520	.568	.628	(.721)	
TSR	5	.874	.585	.374	.477	.507	(.765)

Note. CR = composite reliability; AVE = average variance extracted. Diagonal values (in parentheses) are the square roots of the AVE; off-diagonal values are inter-construct correlations.

Table 4 presents the results for the ABS. Its CR values range from .812 to .880, and AVE values from .520 to .623, supporting construct reliability and convergent validity. Discriminant validity is also supported, as each sub-construct's AVE square root is higher than its correlations with other sub-constructs. These results confirm the measurement model's adequacy for assessing academic buoyancy.

Table 5*Reliability and Discriminant Validity for the Academic Motivation Scale (N = 489)*

Sub-construct	Items	CR	AVE	IM	EM	AMO
IM	11	.945	.611	(.782)		
EM	9	.907	.522	.514	(.723)	
AMO	4	.922	.746	.380	.599	(.864)

Note. CR = composite reliability; AVE = average variance extracted. Diagonal values (in parentheses) are the square roots of the AVE; off-diagonal values are inter-construct correlations.

Table 5 displays findings for the AMS. Sub-constructs yield CR values between .907 and .945, with AVEs ranging from .522 to .746. The square roots of AVEs surpass inter-construct correlations, demonstrating discriminant validity. These metrics confirm the model's reliability and validity for capturing academic motivation.

Academic Performance

Academic performance was assessed using students' academic performance grades (APGs) for the corresponding academic quarter. These were obtained from official school records with the approval of the campus director. Ethical approval was granted by the school administration, and informed consent was secured from all participants. Participant anonymity and data confidentiality were strictly maintained throughout the study.

Limitations

First, although we used total-population sampling ($n = 489$), our study is confined to one STEM high school, limiting generalizability. Second, grades 7–12 were analyzed as a single group; future work should disaggregate by year level to explore developmental differences. Third, while SEM provided robust tests of mediation, causal inferences remain tentative in this cross-sectional design. Finally, despite our CFA steps, self-report instruments are subject to response biases.

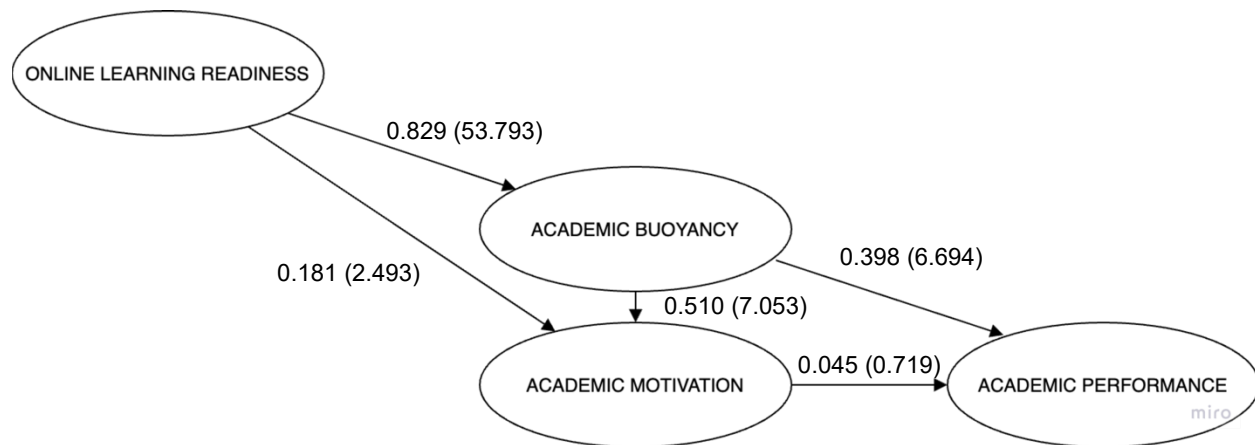
Results and Discussions

Measurement Model

Confirmatory factor analyses of the OLRs, ABS, and AMS instruments demonstrated acceptable model fit indices ($\chi^2/df \leq 2.28$, $RMSEA \leq .051$, $SRMR \leq .062$). All constructs exhibited adequate internal consistency (composite reliability $\geq .80$) and convergent validity (average variance extracted $\geq .50$), confirming the robustness of the measurement model.

Figure 2

Path Analysis Result of the Conceptual Model



Direct Effects

Online learning readiness was hypothesized to directly predict academic buoyancy and academic motivation. As shown in Figure 2, the path from OLR to academic buoyancy was strong and significant ($\beta = .829$, $t = 53.793$, $p < .001$), and the path from academic buoyancy to academic motivation was also significant ($\beta = .510$, $t = 7.053$, $p < .001$). These findings confirm that students who possess strong time-management, self-discipline, and technical self-efficacy skills report higher everyday resilience (Martela & Riecki, 2018), which in turn fosters intrinsic motivation (Deci & Ryan, 2004).

Mediated Effect

The mediation analysis as shown in Table 6 revealed several key findings. First, academic buoyancy significantly mediated the relationship between online learning readiness and academic motivation ($\beta = .423$, $p < .001$), indicating that students who are well-prepared for online learning are more likely to develop motivation through their capacity to handle everyday academic challenges. Similarly, academic buoyancy also significantly mediated the relationship between online learning readiness and academic performance ($\beta = .330$, $p < .001$), suggesting that students who can effectively rebound from setbacks are better able to convert their readiness

into higher academic achievement. In contrast, academic motivation did not significantly mediate the relationship between online learning readiness and academic performance, nor between academic buoyancy and performance, diverging from earlier findings by Horzum et al. (2015). Finally, the full chain mediation pathway—from online learning readiness through academic buoyancy and motivation to academic performance—was also not significant, indicating that while buoyancy plays a crucial role, motivation alone does not fully account for the link between readiness and achievement in this context.

Table 6

Path Coefficients for Mediation (N = 489)

Assumption	Path	β	t	p	LLCI	ULCI	Outcome
A1	OLR $\rightarrow$ AB $\rightarrow$ AM $\rightarrow$ AP	.019	.705	.241	-0.022	0.066	Not Supported
A2	OLR $\rightarrow$ AB $\rightarrow$ AM	.423	7.212	<.001	0.319	0.521	Supported
A3	OLR $\rightarrow$ AB $\rightarrow$ AP	.330	6.195	<.001	0.242	0.413	Supported
A5	AB $\rightarrow$ AM $\rightarrow$ AP	.023	.706	.240	-0.026	0.080	Not Supported
A4	OLR $\rightarrow$ AM $\rightarrow$ AP	.008	.609	.272	-0.009	0.032	Not Supported

Note. OLR = online learning readiness; AB = academic buoyancy; AM = academic motivation; AP = academic performance; LLCI = lower-level confidence interval (95%); ULCI = upper-level confidence interval (95%).

These results indicate that in this high-aptitude STEM context, academic buoyancy, rather than motivation alone, is the more immediate driver of academic performance. Contrary to Horzum et al. (2015), motivation alone did not drive performance in this high-aptitude STEM context during pandemic-era blended learning.

Online Learning Readiness and Academic Buoyancy

The significant OLR $\rightarrow$ AB effect underscores the role of readiness in fostering adaptive academic responses. Students who are better prepared for the demands of online learning tend to exhibit greater resilience in navigating daily academic challenges. This finding is consistent with the control-value theory of achievement emotions and resilience frameworks (Martin & Marsh, 2008; Martela & Riekkari, 2018).

Academic Buoyancy as a Mediator

Academic buoyancy emerged as a critical mediator, transmitting the effects of readiness to both motivation and performance. This finding extends the work of Datu and Yuen (2018) and Yun et al. (2018), showing that buoyancy not only predicts achievement but also channels online learning skills into positive outcomes.

Why Motivation Did Not Mediate Academic Performance

The non-significant mediation effects involving motivation contrast with findings in other educational settings (Ayub, 2010; Datu, 2017). In online learning and STEM environments, motivation may sustain engagement but not necessarily result in higher grades unless scaffolded by resilience and instructional support. This suggests that while academic motivation is crucial for long-term success, buoyancy may serve as the proximate mechanism enabling students to navigate immediate academic demands effectively.

Conclusions

This study highlights the pivotal role of OLR in shaping academic outcomes, primarily through academic buoyancy. Among STEM high school students engaged in online learning, OLR strongly predicted buoyancy, which in turn enhanced both motivation and academic performance. However, academic motivation did not significantly mediate the relationship between readiness and performance, suggesting that resilience is a more salient factor in achievement within this context.

The findings offer empirical support for the indirect-only mediation model: OLR enhances performance *through* buoyancy, not directly or via motivation alone. This implies that interventions targeting online readiness will be most effective when they also explicitly cultivate resilience and emotional adaptability.

Educators should emphasize stress management, recovery from setbacks, and adaptive learning strategies when teaching online readiness skills. Instructional designs must incorporate emotional support mechanisms such as feedback loops and peer discussion forums to reinforce academic buoyancy and help students navigate the challenges of blended learning. School administrators, on the other hand, are encouraged to embed academic buoyancy training within student support services. Readiness assessments can be used to identify students who are at risk of underperforming, allowing institutions to tailor interventions that combine technical skills development with resilience-building strategies. For curriculum designers, it is essential to structure online and blended learning environments in ways that foster autonomy, competence, and relatedness. By offering scaffolded opportunities for collaborative learning, designers can support the translation of students' motivation into measurable academic outcomes.

Recommendations

Basic education institutions should integrate OLR assessments as part of their standard practices to help predict academic risk and personalize instructional support for students. These screenings can inform targeted interventions that address both technical and emotional aspects of learning in digital environments. To further support student success, schools should implement buoyancy-enhancing programs that build students' capacity to manage academic stress and recover from setbacks. Interventions such as workshops on emotional regulation and peer mentoring initiatives can promote resilience and improve students' overall engagement.

Teachers also play a critical role in strengthening students' time management and communication skills. Practical exercises, including planning logs and asynchronous discussion prompts, can be incorporated into instruction to help students better manage deadlines and

express their ideas confidently in online settings. Motivation—both intrinsic and extrinsic—should be nurtured through goal-setting activities, timely and constructive feedback, and the celebration of academic progress. These strategies can sustain students' engagement and commitment throughout the learning process. Finally, ongoing monitoring and feedback are essential. Regular assessment of students' readiness, buoyancy, and motivation enables teachers to proactively adapt their strategies, ensuring continuous support for students' well-being and academic performance.

Declarations

Conflicts of Interest Statement

No conflicts of interest were reported. Ethical approval was obtained from Pampanga State University (formerly Don Honorio Ventura State University), Philippines. Informed consent from parents and assent from students were secured before data collection. Participant confidentiality and anonymity were maintained throughout the study.

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Exploring Psychological Factors Affecting the Success of Online Learning in Higher Education in Indonesia

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Abstract

Online learning in higher education in Indonesia continues to encounter substantial challenges, particularly marked by declining student engagement, increased dropout rates, and the emergence of academic burnout. A shocking phenomenon is the widespread perception of learner apathy, where students demonstrate minimal motivation, reduced participation, and a sense of emotional disconnection from the learning process. These psychological obstacles often undermine the potential of online learning, even when supported by adequate technological infrastructure. Despite these hurdles, online learning remains a necessary and strategic mode of education, especially in bridging geographical disparities across the Indonesian archipelago. Therefore, this study aimed to explore the psychological factors affecting online learning success, including emotional intelligence (EI), psychological well-being (PWB), self-efficacy (SE), and self-motivation (MO), which are believed to be critical in enhancing student engagement and learning outcomes. Engaging 1,052 students in Yogyakarta, the research examined these variables' relationships with online learning success. Online data collection via Google Forms was utilized, with analysis conducted through Structural Equation Modeling (SEM), tested via path analysis and bootstrap. Results indicated that EI, PWB, SE, and MO significantly and positively influenced online learning success. Particularly, MO emerged as an indirect mediator, influencing PWB and SE, thereby enhancing overall online learning effectiveness. This study is pivotal for understanding psychological factors in Indonesian online learning, offering insights into how MO can bolster PWB and SE, ultimately contributing to online learning success. These findings lay a foundation for refining online learning systems, aiming for a more effective and motivating learning environment in the future.

Keywords: Online learning success, emotional intelligence, self-efficacy, self motivation, well-being

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Online learning, defined as an electronic or web-based learning approach, has emerged as a dominant educational model, uniting students, educators, technology, and pedagogical processes (Holmes et al., 2019). Despite its global proliferation, challenges remain, especially in developing nations like Indonesia. The global digital transformation of the 21st century has increasingly normalized online learning across educational settings (Johnson et al., 2022; Rahimi & Oh, 2024), with the COVID-19 pandemic dramatically accelerating its adoption to maintain educational continuity (Hurt et al., 2025; Wagiran et al., 2022).

The roots of online learning can be traced back to educational paradigm shifts beginning in the 1980s, influenced by Dewey's learner-centered ideas from the late 19th and early 20th centuries. This movement laid the foundation for the emergence of online learning. In the 1990s, extensive research began to examine the effects and broader implications of online learning. The digital era has since revolutionized traditional education, placing greater emphasis on student-centered learning environments (Holmes et al., 2019). Innovations such as Massive Open Online Courses (MOOCs) offered by platforms like Coursera and Khan Academy, along with tools such as Google Classroom, have significantly accelerated this transition (Holmes & Gardner, 2006; Nurtanto et al., 2019). Online learning provides a customizable and flexible educational experience, allowing learners to access content anytime and anywhere (Kholifah et al., 2021; Rahimi & Oh, 2024). Moreover, its effectiveness is recognized as being shaped not only by technological aspects but also by psychological and social dimensions (Dziuban et al., 2015; Koletsou & Mancy, 2011).

An in-depth exploration of psychological variables, including emotional intelligence, psychological well-being, self-efficacy, and motivation, is essential to fully understand the determinants of online learning success. These factors significantly affect students' online learning experiences (Ahmad et al., 2021; Chiu et al., 2021), with motivation identified as a critical psychological driver, mediating the relationship between psychological well-being, self-efficacy, and online learning effectiveness (Jatmoko et al., 2023; Tang & Zhu, 2023; Teo et al., 2023).

The efficacy of online learning extends beyond the realm of technological expertise. Psychological dimensions, notably motivation, psychological well-being, and self-efficacy, are crucial for the successful implementation of online learning (Ayal et al., 2021; Koletsou & Mancy, 2011; Vayre & Vonthron, 2017). However, the intricate interconnections among these psychological factors and their combined influence on online learning outcomes have yet to be comprehensively addressed. This study seeks to fill this gap by examining both the direct and indirect effects of emotional intelligence, psychological well-being, and self-efficacy on online learning outcomes, while also investigating the mediating role of motivation.

This research holds significance by providing a thorough analysis of psychological factors that contribute to the success of online learning. It aims to enhance understanding of how emotional intelligence, psychological well-being, and self-efficacy influence online learning, both directly and indirectly, and to illuminate the mediating influence of motivation. This endeavor will offer crucial insights for developing more effective online learning methodologies. Ultimately, as online learning becomes increasingly integral to education, comprehensively analyzing its determinants of success is imperative. This entails not only technological adeptness but also an appreciation for the complex interplay of

psychological factors, thereby enriching the body of knowledge within the online learning research domain.

Literature Review

The theoretical foundation of this study is grounded in the Community of Inquiry (CoI) framework, which conceptualizes meaningful online learning through the interaction of cognitive presence, social presence, and teaching presence (Garrison & Arbaugh, 2007). This framework has been widely recognized as a dominant model in explaining the quality of online learning environments. Building on this perspective, psychological factors such as emotional intelligence (EI), psychological well-being (PWB), self-efficacy (SE), and self-motivation (MO) are positioned as enabling conditions that support the development of these three presences. EI facilitates emotional regulation and social interaction, thereby strengthening social presence. PWB contributes to emotional stability and resilience, which sustain engagement. SE enhances learners' confidence in managing tasks, supporting cognitive presence. Meanwhile, MO drives persistence and active participation, reinforcing all dimensions of the CoI framework. Thus, rather than constituting a separate grand theory, these psychological constructs extend the CoI framework by explaining the internal conditions that enable students to actively engage in collaborative knowledge construction. This integration is particularly relevant in the Indonesian higher education context, where psychological readiness plays a critical role in determining online learning success (Phan & Ngu, 2021; Stark, 2019; Stephen & Rockinson-Szapkiw, 2021; Teo et al., 2023).

Emotional Intelligence on Psychological Well-being and Self-Efficacy

Psychological well-being (PWB) in the context of learning is defined as the optimal state wherein students strive to attain their learning objectives (Kantor & Proekt, 2019). PWB encompasses positive feelings, a sense of meaning in learning, well-being, and the absence of stress symptoms during the learning process. The ability to regulate emotions becomes crucial in influencing students' psychological well-being when engaging in online learning. Furthermore, the capacity to perceive, evaluate, and manage thoughts with positive emotions serves as a fundamental factor in enhancing students' psychological well-being in the online learning setting (Can et al., 2021). A study conducted by Kamboj & Garg (2021) underscores the perception of teachers, indicating that students adept at managing and controlling their emotions exhibit good psychological well-being during learning. Other research affirms that emotional intelligence significantly determines feelings of happiness and high satisfaction levels in learning (Augusto-Landa et al., 2011; Fang et al., 2023). This finding is consistent with the Community of Inquiry perspective, which posits that emotional intelligence enhances both social and cognitive presence, thereby enabling students to sustain engagement in online learning (Redmond et al., 2023; Shea et al., 2022; Yidana & Aboagye, 2024).

Hypothesis 1 (H₁): There is a notable impact of emotional intelligence on psychological well-being. Moreover, a high level of emotional intelligence in students is strongly suggested as a critical factor in elevating student self-efficacy during online learning.

As evidenced by Chang & Tsai (2022), effective management and control of emotions during learning significantly influence confidence levels in problem-solving within the online learning context. Consistent with this, both Wen et al. (2020) and Wang et al. (2020) assert that students' confidence in self-assessment regarding their ability to

achieve learning goals is largely influenced by their emotional control capabilities. Bandura (1982) further supports the idea that self-efficacy continues to grow when accompanied by proper emotional control and management. In online settings, self-efficacy is also enhanced through students' ability to regulate emotional states, which sustains persistence in collaborative learning communities (Shea & Bidjerano, 2010; Stephen & Rockinson-Szapkiw, 2021).

Hypothesis 2 (H₂): There is a substantial effect of emotional intelligence on self-efficacy in online learning environments.

Psychological Well-being and Self-Efficacy in Motivation

Motivation, a crucial psychological aspect for students, necessitates the involvement of other psychological elements to foster its development (Santrock, 2007). These elements must inherently possess characteristics that respond to ongoing life circumstances (Fierro-Suero et al., 2020). Psychological well-being and self-efficacy emerge as key variables that shape how individuals perceive and evaluate their own circumstances. The desired emotional state encapsulated by psychological well-being undoubtedly fuels the growth of motivation in the learning process. Marler et al. (2021) reveal that students' strong inclination to learn is intricately tied to their desired psychological state. Further affirming this link, research by Fierro-Suero et al. (2020) underscores the significant impact of psychological well-being on the flourishing of student motivation. In parallel, another psychological determinant, self-efficacy, plays a crucial role in propelling student learning motivation. Mesa-Fernández et al. (2019) assert that students' drive to learn hinges on robust self-confidence in their learning abilities, particularly evident in the context of mastering online learning. Studies by Alkhatib (2020) and Kong (2021) validate the substantial influence of self-efficacy on the growth of learning motivation in students. This resonates with findings that self-efficacy, reinforced by psychological well-being, predicts stronger engagement in the Community of Inquiry framework, where motivation sustains active participation (de Barba et al., 2016; Shea et al., 2022; Zhang et al., 2025). Additionally, Tang & Zhu (2023); Teo et al. (2023) emphasize the critical role of self-efficacy in fostering student motivation, particularly in the successful implementation of online learning amid the challenges posed by the COVID-19 pandemic.

Hypothesis 3 (H₃): There is a statistically significant relationship between psychological well-being and motivation in online learning.

Hypothesis 4 (H₄): There is a statistically significant relationship between self-efficacy and motivation in online learning.

Psychological Well-being, Self-Efficacy and Motivation for Online learning Success

Online learning success denotes the positive outcomes achieved following the implementation of the learning process through this mode (Ilias et al., 2020; Sun & Chen, 2016). Key success indicators in online learning encompass student satisfaction, positive feedback, enhanced online learning readiness, and the efficiency of materials absorbed by students (Kruger-Ross & Waters, 2013; Sun & Chen, 2016; Wei & Chou, 2020). Crucially, the psychological conditions of students play a pivotal role in the prosperous implementation of online learning (Al-Kumaim et al., 2021; Besser et al., 2022; Li & Wang, 2024). Motivation emerges as a fundamental factor, laying the groundwork for the successful execution of online learning aspects (Berestova et al., 2022; Sun & Chen, 2016).

A robust motivation to engage in online learning positively impacts the willingness to use the platform effectively (Jain & Roy, 2024). Furthermore, as student motivation grows, satisfaction with online learning also experiences an upswing (Stark, 2019). Substantial research underscores the influential role of student motivation in driving online learning success, evident in student readiness and satisfaction during its implementation (de Barba et al., 2016; Stark, 2019).

Hypothesis 5 (H₅): There is a statistically significant relationship between psychological well-being and online learning success.

Aligned with psychological well-being, another critical aspect, self-efficacy, emerges as a determinant of online learning success. students' confidence in their ability to master online learning fosters readiness in its usage. Mesa-Fernández et al. (2019) demonstrate that students' confidence in their ability to master online learning fosters readiness for its use. Correspondingly, research by Kong (2021) and Alkhatib (2020) examines the significant influence of self-efficacy on the effectiveness of understanding learning materials in online environments. Additionally, Wang et al. (2020) highlight the pivotal role of self-efficacy in enhancing student satisfaction, a key benchmark in online learning, particularly during the challenges posed by the COVID-19 pandemic. Research further indicates that self-efficacy contributes directly to cognitive presence and sustained engagement within online communities, reinforcing the success of online learning (Lim et al., 2021; Vayre & Vonthron, 2017).

Hypothesis 6 (H₆): There is a statistically significant relationship between self-efficacy and online learning success.

Lastly, motivation, identified by experts as a vital psychological aspect, profoundly influences the implementation of online learning (Chiu et al., 2021; Stark, 2019). Within the online learning context, motivation is defined as the driving force compelling an individual to navigate the processes of the online learning system using accessible devices to achieve learning objectives (Marler et al., 2021). Research by Tang & Zhu (2023), Stark (2019) and Teo et al. (2023) underscores the pivotal role of motivation in enhancing student readiness for online learning implementation. Meanwhile, Chiu et al. (2021) and Jain & Roy, 2024), emphasize the paramount importance of motivation in ensuring the success of online learning, substantiating its significant influence on implementation success. Motivated learners contribute more actively to collaborative inquiry and knowledge construction, reflecting the essential role of motivation in the CoI framework (Liu & Yang, 2014; Yidana & Aboagye, 2024).

Hypothesis 7 (H₇): There is a statistically significant relationship between motivation and online learning success.

Mediating Roles of Motivation

Psychological aspects, particularly psychological well-being and self-efficacy have been widely acknowledged to significantly influence e-learning success both directly and indirectly (Santrock, 2007). In terms of indirect influence, previous studies emphasize that psychological well-being enhances learning outcomes by fostering higher motivation. Among various psychological factors, intrinsic motivation is a key driver that encourages students to engage actively in online learning without external pressure (Wang et al., 2020). The Self-Determination Theory (Ryan & Deci, 2000) and the Expectancy-Value Theory (Eccles & Wigfield, 2020; Martin et al., 2021) explain that motivation acts as a bridge

linking psychological well-being with successful learning outcomes by promoting autonomy, competence, and meaningful engagement.

Empirical studies have confirmed that students with higher psychological well-being, reflected in optimism, purposefulness, and feelings of value, are more likely to achieve success in online learning (Morales-Rodríguez et al., 2020; Zou et al., 2023). Conversely, insufficient motivation and lower well-being levels can disrupt the learning process and reduce academic success (Fiorella, 2020; Lyboldt et al., 2023; Rüppel et al., 2015). Given these findings, it becomes essential to validate this relationship within the Indonesian context, where educational dynamics may differ.

Hypothesis 8 (H₈): Psychological well-being has a significant impact on e-learning success through the mediating role of motivation.

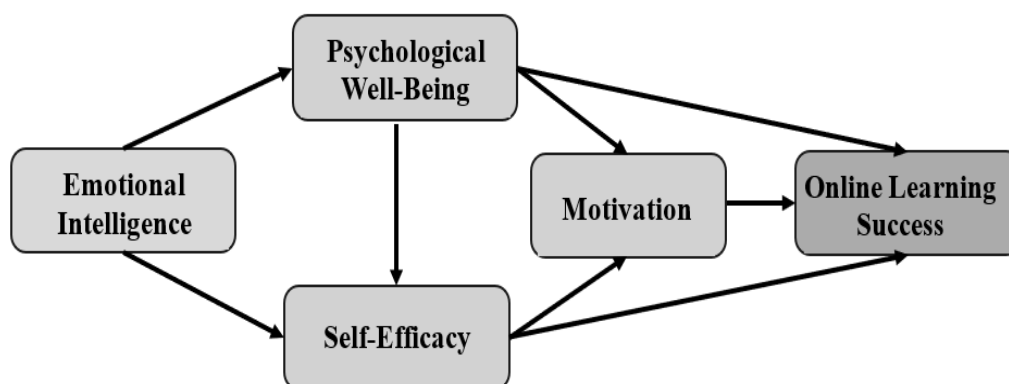
Beyond psychological well-being, self-efficacy is another crucial psychological factor that influences success in online learning environments. Students with strong self-efficacy, who are optimistic about achieving learning goals, confident in solving problems, and believe in their capacity to learn across disciplines, generally show better online learning performance (Bandura, 1982; Kholifah, Kurdi, Nurtanto, & Mutohhari, 2023). Prior studies Stephen & Rockinson-Szapkiw (2021); Zimmerman & Kulikowich (2016) further support that high self-efficacy enables students to manage online learning challenges effectively. However, high self-efficacy alone does not guarantee learning success, especially when motivation is unstable or external supports are lacking (Schunk, 1985; Zimmerman, 2000). Instability in motivation can reduce student persistence and performance during online education. To strengthen the empirical understanding in this area, particularly within the Indonesian context, the following hypothesis:

Hypothesis 9 (H₉): Self-efficacy significantly influences e-learning success through the mediating role of motivation.

Figure 1 illustrates a conceptual model of online learning success through psychological well-being, self-efficacy, and motivation. furthermore, emotional intelligence directly correlates with psychological well-being and self-efficacy and is predicted to influence online learning success.

Figure 1

Mediation Model of Self-Regulation in Terms of the Relationship Between Adaptability and Student Engagement



Methods

Research Design

In this research, the impact of the independent variable on the dependent variable was assessed through a quantitative data approach. The focus was on the collected data, and the structural equation modeling (SEM) technique was employed for analysis, both with and without a mediator, supported by robust theoretical foundations. The study adopted an ex-post facto design based on structural data (Cohen et al., 2011). It involved Indonesian university students who had the prerequisite of engaging in online learning for two to four semesters. Utilizing a university academic monitoring and assessment system, an online questionnaire was administered to gather comprehensive data on all variables. The monitoring and assessment period, spanning from April to June 2022, aligned seamlessly with the study.

Participants

In this study, participants consisted of undergraduate students in Yogyakarta Province, Indonesia. The selection criteria focused on students who had experienced online learning for two to four semesters, ensuring sufficient exposure to explore diverse opinions on the psychological aspects influencing successful online learning implementation. A total of 126 invalid responses, including identical answers and completion times under 30 seconds, were removed to ensure questionnaire diversity. The final sample comprised 1,052 students, representing a 92% response rate from the predetermined sample. Yogyakarta Province universities contributed 1052 participants. Background statistics, including gender, age range, majors, and weekly online learning intensity, are detailed in Table 1.

Table 1

Background of Participants (N=1,052)

Dimensions	Category	Frequency	Percentage
Gender	Male	594	56.46%
	Female	458	43.54%

Dimensions	Category	Frequency	Percentage
Study period	1– 4 semesters	448	42.59%
	5 – 8 semesters	394	37.45%
	9 – 12 semesters	162	15.40%
	13 – 14 semesters	48	4.56%
Expertise	Tourism	323	30.70%
	IT	348	33.08%
	Technology and Engineering	381	36.22%
Online Learning	8 – 12 hours	139	13.21%
	13 – 17 hours	166	15.78%
Intensity	18 – 22 hours	319	30.22%
	23 – 27 hours	528	50.19%

Data Collection and Instruments

The study's data collection process was anchored in the utilization of each university's monitoring and evaluation system, known as e-monev. Focusing on students who participated in at least 40 hours of online learning from April to June 2022, the integration of e-monev with the Academic Information System (AIS) mandated the completion of an online learning readiness survey on the platform's landing page. To enhance the reliability of data collection, socialization and briefing sessions were organized before the actual data collection, aiming to ensure data accuracy and coherence. The survey employed a Likert scale for responses, with options ranging from *strongly disagree (SD)* to *strongly agree (SA)*, for evaluating various factors. The survey questions, derived from previously validated scales, were subjected to confirmatory factor analysis, confirming the reliability and validity of the measurement instrument.

Six statements capturing emotional intelligence encompass expressions like

- *I am mindful of my emotions in the moment.*
- *I can discern others' feelings by observation.*
- *I engage in activities that bring me joy.*
- *I know when to discuss my concerns with others.*
- *I uplift those feeling down.*
- *I leverage positive moods to maintain my spirits.*

Originating from the works of Chang & Tsai (2022) and Pienimaa et al. (2021), these indicators were crafted to evaluate emotional intelligence.

Psychological well-being is measured through three opinion-based indicators, reflecting sentiments such as

- *I consistently maintain optimism in online learning activities.*
- *Online learning activities hold purpose and meaning for me.*
- *I feel respected and valued by others in the online learning environment*

These indicators, designed by Morales-Rodríguez et al. (2020) and Zhang et al. (2022), contribute to assessing psychological well-being.

Self-efficacy is measured through three opinion-based indicators, reflecting students' confidence in their learning abilities, such as:

- *I am optimistic about achieving learning goals.*
- *I have confidence in my problem-solving abilities.*
- *I believe in my capacity to learn multidisciplinary science through online learning.*

These indicators are adapted from Bandura (1982) and Kholifah et al. (2023) to assess students' self-efficacy in online learning contexts.

Motivation is measured through five indicators, reflecting students' drive and persistence in learning, such as:

- *I can maintain focus on learning despite distractions.*
- *I eagerly embrace new challenges and learning opportunities.*
- *I am enthusiastic and prepared to tackle learning problems through online learning.*
- *I am consistently motivated to complete learning assignments.*
- *I am open to exploring diverse learning resources in online learning.*

These indicators are adapted from Stark (2019) to capture students' motivation in online learning environments.

Online learning success is measured through seven indicators, reflecting students' perceived effectiveness and outcomes in online learning, such as:

- *I possess the ability to use information and communication technology (ICT) effectively.*
- *I am confident in organizing and conducting learning via the internet.*
- *I can effectively communicate using internet and ICT networks.*
- *I have control over and can explore online learning content.*
- *I am satisfied with the infrastructure supporting online learning.*
- *I can attain learning outcomes in online learning.*
- *I can enhance my skills through online learning.*

These indicators are adapted from Adams et al. (2022) and Stark (2019) to assess overall online learning success.

Validity and Reliability of Instruments

Prior to the large-scale survey, a pilot test of the variables was conducted using a subset of the sample to ensure the instrument's clarity and appropriateness. The preliminary dataset was analyzed to examine internal consistency and reliability. Cronbach's Alpha values were calculated for each construct, and all exceeded the recommended threshold of 0.70, indicating acceptable to high reliability (Johnson & Wichern, 2007). This procedure ensured that the items within each construct were internally consistent and adequately represented the intended psychological factors. Furthermore, construct validity was assessed by expert review and pilot responses, confirming that the items aligned with the

theoretical framework. Only after this pilot testing phase was the instrument finalized and administered in the full-scale data collection. The comprehensive validity test outcomes are depicted in Table 2.

Table 2

Validities of Instruments for Emotional Intelligence, Psychological Well-Being, Self-Efficacy, Motivation, and Online Learning Success

Variable	Item	Outer Loading	Desired level	Decision
Emotional Intelligence	EI1	0.810	≥ 0.700	Valid
	EI2	0.775	≥ 0.700	Valid
	EI3	0.846	≥ 0.700	Valid
	EI4	0.867	≥ 0.700	Valid
	EI5	0.833	≥ 0.700	Valid
	EI6	0.759	≥ 0.700	Valid
Psychological Well-Being	PWB1	0.811	≥ 0.700	Valid
	PWB2	0.897	≥ 0.700	Valid
	PWB3	0.910	≥ 0.700	Valid
Self-Efficacy	SE1	0.849	≥ 0.700	Valid
	SE2	0.887	≥ 0.700	Valid
	SE3	0.859	≥ 0.700	Valid
Motivation	Mo1	0.737	≥ 0.700	Valid
	Mo2	0.843	≥ 0.700	Valid
	Mo3	0.833	≥ 0.700	Valid
	Mo4	0.727	≥ 0.700	Valid
	Mo5	0.771	≥ 0.700	Valid
Online Learning Success	ELS1	0.890	≥ 0.700	Valid
	ELS2	0.897	≥ 0.700	Valid
	ELS3	0.886	≥ 0.700	Valid
	ELS4	0.801	≥ 0.700	Valid
	ELS5	0.832	≥ 0.700	Valid
	ELS6	0.730	≥ 0.700	Valid
	ELS7	0.866	≥ 0.700	Valid

The reliability test results are equally satisfactory. Demonstrating high standards across all instruments, the alpha reliability test outcomes are detailed in Table 3, underscoring the instruments' consistent data collection capabilities.

Table 3

Reliabilities of Instruments for Emotional Intelligence, Psychological Well-Being, Self-Efficacy, Motivation, and Online Learning Success

Variable	α	ρ_A	Composite	AVE	Decision
Emotional Intelligence	0.899	0.903	0.923	0.665	Reliable

Variable	α	ρ_A	Composite	AVE	Decision
Psychological Well-being	0.844	0.848	0.906	0.763	Reliable
Self-efficacy	0.832	0.833	0.899	0.749	Reliable
Motivation	0.842	0.846	0.888	0.614	Reliable
Online Learning Success	0.933	0.940	0.946	0.714	Reliable

Data Analysis and Ethical Considerations

To analyze the hypotheses concerning the influence of various variables, this study utilized Structural Equation Modeling (SEM). Path analysis facilitated the assessment of how exogenous variables directly affect endogenous ones. Additionally, the mediating effect of motivation on the indirect impact of psychological well-being and self-efficacy on online learning efficacy was examined using a bootstrap method. This method is crucial for determining the robustness and reliability of indirect effects in diverse situations, as it aids in establishing confidence intervals (Preacher & Hayes, 2008). The SmartPLS 3.0 software was chosen for data analysis. The formulation of research hypotheses was guided by a comprehensive review of existing literature, highlighting the direct or indirect influence of external factors on internal variables.

This study was conducted in accordance with the principles of the Declaration of Helsinki. It was approved by the Ethics Committee of the Institute for Research and Community Service at Universitas Negeri Jakarta (approval number: 18/UN39.14/PT.01.06/I/2022, dated January 8, 2022). All participants were fully informed about the study's objectives, the voluntary nature of their participation, and the confidentiality of their responses. Written informed consent was obtained prior to participation. Transparency was ensured in the development and validation of the research instruments. Respondents participated voluntarily without coercion, and they were assured that their responses would be used solely for academic purposes. Moreover, participants retained the right to withdraw from the study at any stage without penalty, thereby safeguarding their autonomy, rights, and well-being.

Results

Structure Model Analysis

The assessment of the structural model's conformity level was conducted through a model appropriateness test. Table 4 illustrates the overall fit indices of the research model, serving as the baseline model. Notably, the basic model demonstrated commendable performance in terms of overall fit. The chi-square value computed was relatively modest, with a highly significant probability achieved. Key fit indices, including GFI, AGFI, NFI, SRMR (0.05), and RMSEA (0.08), surpassed the accepted threshold of 0.90. These results affirm the suitability of the fit model within the goodness of fit category, enabling the commencement of structural model analysis (Johnson & Wichern, 2007).

Table 4
Model Fit Test Result

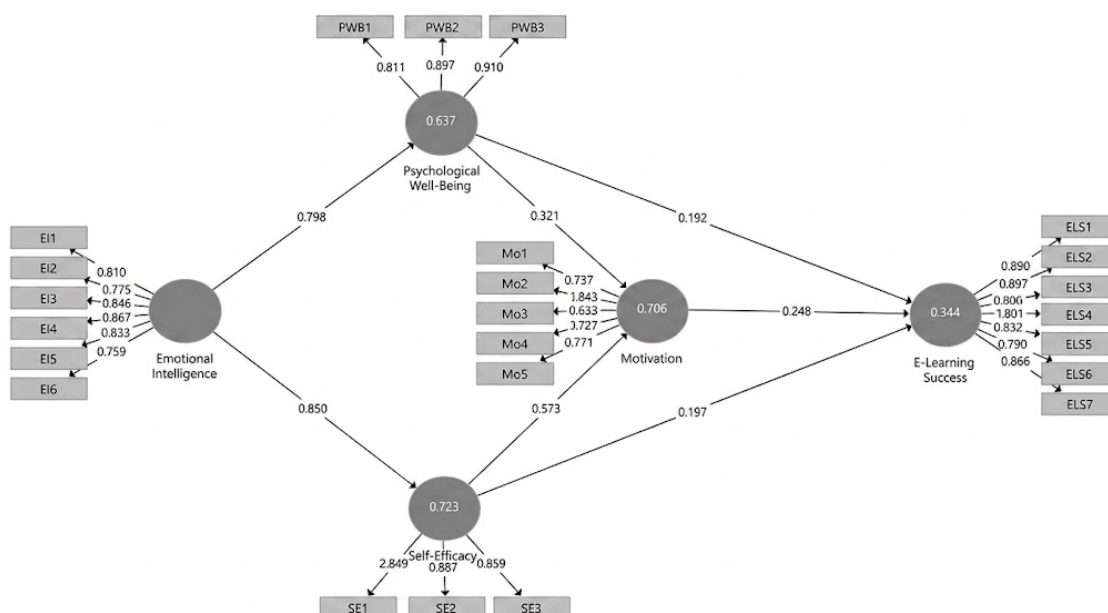
Goodness of fit indices	Result	Desired levels
Chi-square	31.501	Small
Probability	0.418	>0.50

Goodness of fit indices	Result	Desired levels
GFI	0.914	≥ 0.90
AGFI	0.931	≥ 0.90
NFI	0.921	≥ 0.90
SRMR	0.036	< 0.05
RMSEA	0.048	< 0.08

Figure 2 portrays the structural analysis model implemented in the study. Both path analysis and SEM analysis were employed to evaluate the direct impact of exogenous factors on endogenous variables. Furthermore, the bootstrap method was applied to examine the role of intervening factors in the model.

Figure 2

Structural Model Analysis Results for Emotional Intelligence, Psychological Well-Being, Self-Efficacy, Motivation, and Online Learning Success



Direct Effect Test

The scrutiny of direct effects is elucidated through the revelations of path analysis, encompassing the estimated impact values on the original sample, the t-count value, and the probability value at the 5% or 95% confidence level. The hypothesis testing pertains to the influence of emotional intelligence on psychological well-being and self-efficacy, the effects of psychological well-being and self-efficacy on motivation and online learning success, and the impact of motivation on online learning success.

Table 5

Path Analysis Test Result

Path	Estimate	t value	Bias	p
Emotional Intelligence → Psychological Well-Being	0.798	60.402	0.000	0.000

Path	Estimate	t value	Bias	p
Emotional Intelligence → Self-Efficacy	0.850	80.739	0.000	0.000
Motivation → Online Learning Success	0.248	4.622	0.001	0.000
Psychological Well-Being → Online Learning Success	0.192	4.361	-0.001	0.000
Psychological Well-Being → Motivation	0.321	10.050	-0.001	0.000
Self-Efficacy → Online Learning Success	0.197	4.127	-0.001	0.000
Self-Efficacy → Motivation	0.573	19.603	0.000	0.000

The entire sample underwent the hypothesis tests, stratified into groups based on participants' backgrounds. Testing was conducted across each dimension in the background to ascertain the testability of the hypotheses in all respondents with the diverse features presented. Table 5 delineates the outcomes of hypothesis testing through route analysis on the overall sample, while Table 6 delineates samples contingent on each dimension in the participants' background.

The findings support Hypothesis 1 (H₁), showing a direct and significant influence of emotional intelligence on psychological well-being, evidenced by an estimated coefficient of 0.798 and a p-value of less than 0.001. Emotional intelligence also significantly affects self-efficacy, corroborating Hypothesis 2 (H₂), with an estimated coefficient of 0.850 and a p-value of less than 0.001. In line with Hypothesis 3 (H₃), psychological well-being is shown to significantly impact motivation, with an estimated coefficient of 0.321 and a p-value of less than 0.001. Furthermore, self-efficacy significantly influences motivation, validating Hypothesis 4 (H₄), with an estimated coefficient of 0.573 and a p-value of less than 0.001. Hypothesis 5 (H₅) is confirmed by an estimated coefficient of 0.192 and a p-value of less than 0.001, indicating a direct effect of psychological well-being on online learning success. Additionally, Hypothesis 6 (H₆) finds support through the direct effect of self-efficacy on online learning performance, with an estimated coefficient of 0.197 and a p-value of less than 0.001. Motivation's significant influence on online learning outcomes is confirmed by Hypothesis 7 (H₇), with an estimated coefficient of 0.248 and a p-value of less than 0.001. The consistent significance across all hypotheses, indicated by p-values below 0.050, highlights a pervasive impact across the sample and underscores the necessity of integrating emotional intelligence, psychological well-being, self-efficacy, and motivation for the best educational results.

Indirect Effect Test Through Self-Motivational as Mediation

This study investigates the indirect effects of psychological well-being and self-efficacy on online learning success, specifically examining the mediating role of motivation. Through statistical analysis using the SmartPLS software, the bootstrap method with a 97.5% confidence interval is applied to determine precise confidence limits for various cases. This method effectively confirms the significant mediating role of motivation (Preacher & Hayes, 2008). Table 6 highlights the critical role of motivation in mediating the relationship between psychological well-being and online learning achievement. An indirect effect value of 0.079 with a significance level of less than 0.001 indicates the extent to which psychological well-being affects online learning efficacy through motivation. This

suggests that psychological well-being, facilitated by motivation, indirectly influences online learning effectiveness, supporting Hypothesis 8 (H₈).

Table 6

Mediation Effect of Motivation Between Psychological Well-Being and Online Learning Success

	ELS		Mo		Estimate	<i>p</i>	Bootstrapping 97.5% CI	
	Estimate	S.E.	Estimate	S.E.			Lower limit	Upper limit
PWB	0.192	0.018	0.321	0.031				
SE			0.224	0.044				
F ²	0.489		0.471					
Indirect effect					0.079	0.000	0.042	0.108
Direct effect					0.192	0.000	0.167	0.226
Total effect					0.271	0.000	0.198	0.298

Note: PWB = Psychological Well-Being; SE = Self-Efficacy ELS = Online learning Success; MO = Motivation

Similarly, as depicted in Table 7, motivation assumes a pivotal role in mediating the indirect influence of self-efficacy on online learning performance. The estimated value of 0.142, coupled with a significance of 0.000, attests to the support for H₉.

Table 7

Mediation Effect of Motivation Between Self-Efficacy and Online Learning Success

	ELS		Mo		Estimate	<i>p</i>	Bootstrapping 97.5% CI	
	Estimate	S.E.	Estimate	S.E.			Lower limit	Upper limit
SE	0.197	0.019	0.573	0.024				
ELS			0.314	0.017				
F ²	0.632		0.541					
Indirect effect					0.142	0.000	0.098	0.188
Direct effect					0.197	0.000	0.167	0.241
Total effect					0.339	0.000	0.297	0.374

Note: PWB = Psychological Well-Being; SE = Self-Efficacy ELS = Online learning Success; MO = Motivation

Discussion

Over the course of the prolonged COVID-19 pandemic, college students' attitudes and behaviors toward online learning have undergone a substantial transformation. The surge in online learning usage is attributed to a strategy of initial defense and subsequent adaptation (Adams et al., 2022; J. Wang et al., 2024). In our sample, a majority of students (over 50%) have proactively adapted by intensifying their use of online learning, dedicating

approximately 23-27 hours per week. This suggests a shift in students' preferences from traditional classroom settings to digital learning (virtual classrooms). However, a segment of students has struggled to make significant adjustments, maintaining an online learning intensity within the range of 8-12 hours per week.

Conversely, some students surpass the standard Indonesian graduation timeframe of eight semesters, indicating potential challenges in completing their studies. Despite the diverse nature of the sample, the data generated reflects this variability, albeit not uniformly distributed. This study underscores the significance of psychological factors, including emotional intelligence, psychological well-being, self-efficacy, and motivation, in influencing online learning performance. Furthermore, motivation emerges as a crucial mediator for the impact of psychological well-being and self-efficacy on the effectiveness of online learning implementation.

These findings contribute to the broader body of online learning literature by highlighting the importance of psychological readiness as a determinant of success, consistent with the Community of Inquiry (CoI) framework (Garrison & Arbaugh, 2007). While prior studies have emphasized the role of technological readiness and access (de Barba et al., 2016; Yilmaz, 2016), our results extend the literature by demonstrating that emotional intelligence and psychological well-being are equally critical for sustaining social and cognitive presence online. This positioning enriches theoretical understanding, as it suggests that online learning success cannot be separated from learners' psychological capital, thereby expanding the scope of CoI beyond its original focus on pedagogy and interaction.

Interestingly, the results reveal that self-motivation plays a stronger mediating role than initially anticipated, amplifying the effects of psychological well-being and self-efficacy. This finding is consistent with Stark (2019) and Teo et al. (2023), who highlight the central role of motivation in sustaining engagement. However, the present results indicate that motivation not only supports engagement but also converts the influence of other psychological factors into measurable learning outcomes. Conversely, the relatively weaker direct effect of psychological well-being on learning success was unexpected, indicating that well-being alone is insufficient unless reinforced by strong motivational dynamics. This nuance challenges earlier assumptions that well-being directly predicts online learning performance (Rodríguez et al., 2020), instead highlighting its indirect but essential contribution.

From a theoretical perspective, the study advances online learning research by integrating psychological constructs into the CoI framework, thereby proposing a more holistic model of online learning success. This synthesis demonstrates that psychological capital (EI, PWB, SE, and MO) underlies the conditions for meaningful presence and engagement. Practically, these findings have implications for higher education institutions: interventions to improve online learning should not only focus on infrastructure but also include training in emotional intelligence, resilience programs to enhance well-being, and pedagogical strategies to strengthen students' self-efficacy and motivation (Bagdy & Stefaniak, 2024; Stephen & Rockinson-Szapkiw, 2021; Wagiran et al., 2022). Without these psychological supports, even well-designed online platforms risk disengagement and dropout.

Moreover, our findings refine the discourse on equity in online learning. Students with lower psychological capital may face compounded disadvantages, especially in

contexts where academic support is limited. This insight resonates with Besser et al., (2022), who highlighted adaptability as a challenge during sudden online transitions, and suggests that sustainable online education in developing countries like Indonesia requires policies that simultaneously address psychological and technological readiness. Failure to do so may exacerbate digital divides and academic inequalities.

In sum, this study both confirms and extends prior scholarship. It confirms the importance of motivation and self-efficacy as repeatedly reported in online learning studies (Di Fabio & Kenny, 2016; Sanchez-Ruiz et al., 2021), while extending the literature by positioning emotional intelligence and well-being as foundational yet indirect contributors. Theoretically, it challenges narrow interpretations of CoI by embedding psychological capital as a prerequisite for presence. Practically, it calls for higher education policy and practice to treat psychological supports as essential infrastructure for sustainable online learning ecosystems.

Several limitations of this study should be acknowledged. First, the data were collected from a single region in Indonesia, which may limit the generalizability of the findings to broader cultural or institutional contexts. Second, the psychological constructs were measured using self-report questionnaires with a limited number of items, which may not fully capture the multidimensional nature of emotional intelligence, psychological well-being, self-efficacy, and motivation. Third, the cross-sectional design restricts the ability to infer causality between variables. Additionally, while efforts were made to validate the instrument, further psychometric testing with larger and more diverse samples is recommended for future research. These limitations suggest that caution should be exercised in interpreting the results and that replication studies across different higher education settings are needed.

From a methodological perspective, the study employed a survey-based quantitative approach, which provides broad insights but may overlook the nuanced, qualitative experiences of learners in online environments. The reliance on self-reported data also presents the possibility of social desirability bias. Future studies are encouraged to adopt mixed-method designs to provide deeper contextual understanding and triangulate quantitative findings with qualitative evidence. Addressing these methodological constraints is essential to strengthening the validity and applicability of future research in this field.

Conclusion

The educational landscape witnessed a transformation in college students' cognitive processes and behaviors amid the prolonged COVID-19 pandemic, particularly in response to online learning. Students' psychological factors played a pivotal role in shaping these shifts in mental processes and behavior within the realm of online learning. As indicated by existing literature, essential psychological attributes, including emotional intelligence, psychological well-being, self-efficacy, and motivation, form the bedrock for the successful integration of online learning within university settings. Notably, motivation emerges as a paramount psychological determinant, influencing both the success of online learning and serving as a mediator for the indirect impact of psychological well-being and self-efficacy on online learning effectiveness. In this context, higher education institutions are urged to prioritize the consideration of psychological variables that underpin the efficacy of online learning, rather than exclusively concentrating on skill development. Initiating this emphasis right from the initial lectures, higher education can proactively nurture and mold

emotional intelligence. Additionally, addressing students' psychological well-being needs and fostering self-efficacy are imperative steps in enhancing learning motivation during online learning, ultimately ensuring its successful adoption.

Declarations

The author declares no conflicts of interest. Permission to collect data from human subjects was granted from the authors' educational institutions.

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MOOC Videos in the Age of Streaming: Learner Preferences and Perceptions

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Abstract

Massive Open Online Courses (MOOCs) have become a significant medium for global education, with video lectures (MVLs) serving as a cornerstone of content delivery. This study investigates how learners perceive affect, cognition, and social cues in MVLs, analyzing 2,239 learner-generated reviews (student evaluations) across 25 courses using a qualitative approach. The findings emphasize the lecturer's role as both an educator and performer, highlighting their capacity to inspire and engage through charisma, humor, and clarity. Learners also approach MVLs in a *want-to-learn* streaming culture, blending educational motivation with entertainment-like consumption patterns. Social presence, achieved through conversational tones and non-verbal cues, fosters a sense of connection, while shorter, high-quality videos enhance cognitive engagement. These insights are contextualized within the CASTLE framework, offering practical recommendations for MOOC design and theoretical contributions to understanding digital learning environments.

Keywords: MOOC; perception; cognition; affect; social cues; video lectures

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Massive Open Online Courses (MOOCs) have revolutionized access to education by providing flexible, scalable learning opportunities to diverse global audiences (Sultan, 2019). Central to the MOOC experience is MOOC video lectures (MVLs), which serve as both the primary content delivery method and a critical factor influencing learner engagement and satisfaction (Crook & Schofield, 2017). Recent research has explored various dimensions of MOOC effectiveness, including the role of motivation, cognitive engagement, and social presence (Deng & Gao, 2023). However, limited attention has been paid to how learners perceive the interplay of affective, cognitive, and social cues in MVLs, particularly the role of lecturers and learners' evolving consumption behaviors.

This study addresses this gap by analyzing learner reviews from 25 MOOCs to understand how MVLs foster or hinder engagement. Grounded in the cognitive-affective-social theory of learning in (digital) environments (CASTLE: Schneider et al., 2022) framework, the study explores three dimensions: affect, cognition, and social connection, with a specific focus on the lecturer's dual role as an educator and performer. By examining how learners consume MVLs in a "want-to-learn" (Fischer, 2014) streaming-like culture, the study provides actionable insights for MOOC practitioners and theoretical advancements in digital learning research.

Literature Review

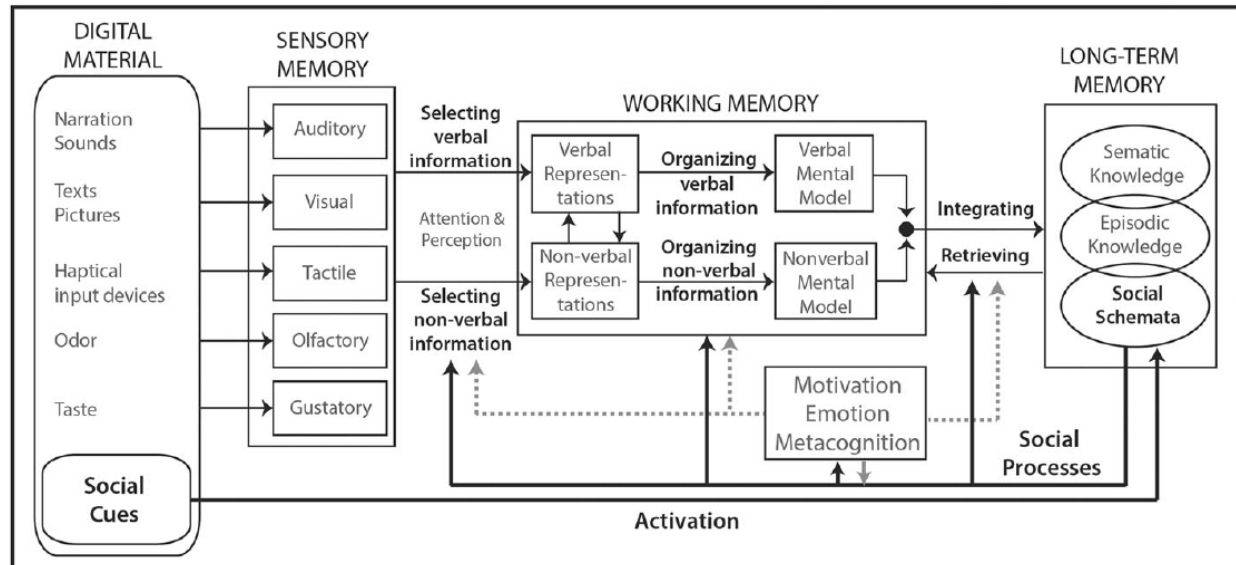
Cognitive-Affective-Social Theories of Learning

Cognitive load theory (CLT; Sweller & Chandler, 1991; Paas & Ayres, 2014) describes how learners process information through sensory, working, and long-term memory, with the finite capacity of working memory as a key constraint. CLT distinguishes intrinsic, extraneous, and germane load. Effective instructional design aims to reduce extraneous load while supporting germane processing. Building on CLT, the *cognitive theory of multimedia learning* (CTML; Mayer, 2024) proposes that audio and visual information is processed through dual channels and integrated into long-term memory. Subsequent work extends these cognitive accounts by incorporating affect and social facilitation: Moreno's (2007) *cognitive affective theory of learning with media* (CATLM) incorporates motivation and affect; Plass et al. (2014) show that appealing design elements can evoke positive emotions that support comprehension; and the *augmented cognitive load theory* (aCLT; Huk & Ludwigs, 2009) emphasizes how cognitive and affective mechanisms work together. *Social agency theory* (Mayer et al., 2003), meanwhile, adds that social cues in learning artifacts can foster rapport and support learning, particularly when instructors are visible.

Tying these perspectives together is the *cognitive-affective-social theory of learning in (digital) environments* (CASTLE; Schneider et al., 2022). CASTLE explains learning from digital materials as shaped by cognitive processing alongside social processes triggered by social cues. These cues activate social schemata, which can foster metacognition, emotional connection, motivation, and perceptions of social connection. CASTLE builds on CLT and CTML and adds the *social mediation hypothesis*: "social processes triggered by social cues mediate the cognitive processing of information when learning with digital materials" (p. 8). In this view, learning is more likely when materials evoke social and para-social processes that interact with motivation, emotion, and metacognition (Figure 1).

Figure 1

The Cognitive-Affective-Social Theory of Learning in (Digital) Environments (Schneider et al., 2022)



Note. While the original comprehensive model includes all sensory inputs (including odor/taste), this study focuses specifically on the visual and auditory cues relevant to video lecture consumption.

In CASTLE, the number and strength of social cues embedded in digital material shape the degree to which social processes are activated. In addition, learners may differ in how readily social schemata are activated, making social processes more or less influential in supporting cognitive processing. Dynamic digital learning materials may contain greater social traces and so may be more likely to elicit these processes. This theory is particularly relevant for studying MOOCs and video lectures because it offers a framework to assess how learners perceive and process video content that promotes affect, cognition, and social connection.

Applying CASTLE to MVL Research

CASTLE provides a targeted framework for this study by explaining how social cues in digital media trigger social and parasocial processes that, in turn, shape cognition and affect. Drawing on Schneider et al.'s activation and cognitive influence hypotheses, we conceptualize learners' references to clarity, organization, and understanding as evidence of social processes mediating selection, organization, and integration of information in MVLs. Likewise, their reports of enjoyment, boredom, warmth, and detachment reflect the interaction hypothesis, in which motivational and emotional states are intertwined with socially cued processing. Because video lectures are dynamic, visually and aurally rich artifacts, they carry a relatively high "social trace," making them especially likely to elicit social presence and parasocial interaction through eye gaze, gesture, voice, and conversational language. In this study, we therefore use CASTLE not only as a broad lens but as a set of guiding assumptions for coding affective, cognitive, and social references in learner reviews and for interpreting how lecturer performance, production choices, and design elements jointly shape learning in MOOCs.

Studies Into MOOC Learner Perceptions

Prior research on MOOC learners' perceptions of video lectures points to three recurring sets of factors: *affective*, *cognitive*, and *social*.

Affective Factors

Videos designed with emotionally engaging features, such as storytelling, humor, and visually appealing content, can reduce cognitive load and sustain attention (Wong & Adesope, 2021). Deng and Gao (2023), for example, analyzed 4,534 learner reviews from a Chinese University MOOC platform using MAXQDA and found that learners appreciated instructors who incorporated humor and made content relatable, particularly in technical subjects. Personalization can also contribute to emotional engagement; learners respond positively to videos that use conversational language and personal anecdotes, fostering relevance and connection (Hew, 2016). Emotional design features (e.g., warm colors, inviting graphics, and human-centered storytelling) have been shown to increase intrinsic motivation and enjoyment, particularly in career-oriented courses (Peng & Jiang, 2022), and positive emotional responses may support persistence in MOOCs (Henderson & Schroeder, 2021). However, overly emotional designs may alienate learners who prefer a straightforward, fact-based approach. Lawson et al. (2021) caution against overusing dramatic or whimsical elements, for example, as this can detract from perceived credibility.

Cognitive Factors

Cognitive engagement with MVLs depends on clarity, organization, and interactivity. Ou et al. (2019) propose a seven-principal model for video design that integrates instructional methods with presentation style to reduce cognitive load, emphasizing practices such as signaling and segmentation to maintain engagement in asynchronous environments. Learners consistently value these elements. Deng and Gao (2023) identified “organized,” “detailed,” and “comprehensible” as key attributes of MOOC videos. Logical structuring, clear explanations, and step-by-step demonstrations support comprehension, and incremental progression from basic to advanced topics can help mitigate cognitive overload (Guo et al., 2014). Video length is another important factor, with shorter videos (typically 5–10 minutes) often associated with stronger engagement (Zhang et al., 2021) and higher completion and likelihood to replay and review (Guo et al., 2014). Connections to quizzes and external resources can further support cognitive engagement by helping learners consolidate and self-assess understanding (Vural, 2013), and supplemental materials such as slides, readings, and post-video assessments are frequently cited as valuable supports (Shah et al., 2022). When videos are too dense, integrating multimedia elements (e.g., diagrams and animations) and using signposting (headings, transitions, highlights) can help manage cognitive load and support retention (Mayer, 2021; Hew et al., 2018).

Social Factors

Social presence in MVLs can shape learners' sense of connection and community, which is often constrained in MOOCs because participation is typically asynchronous and solitary.

Instructor-visible videos, conversational delivery, and interactive prompts can reduce this sense of isolation by strengthening interpersonal connection (Alemdag, 2022). Lawson et al. (2021) found that learners perceived videos with instructors on-screen as more engaging and trustworthy, even when the content was unchanged. Learners also respond to instructors' enthusiasm and authenticity, which can foster confidence and motivation (Hew et al., 2018). Social connection can be further supported when MVLs are integrated with discussion and collaborative activities that prompt interaction with peers (Deng & Gao, 2023), and course-level features such as forums, peer feedback, and group projects can complement MVLs by providing spaces for interaction and reflection (Shah et al., 2022). At the same time, learners may still prioritize clarity and relevance, so social features should support rather than compete with instructional goals (Zhang et al., 2021).

Research Questions

The literature reviewed shows that learners' positive and negative perceptions of MOOCs can be detected in reviews. This paper uses CASTLE (Schneider et al., 2022) as a conceptual framework to interpret how learners perceive affective, cognitive, and social cues in MVLs. Therefore, RQ1 asks: How do learners perceive the role of affective, cognitive, and social cues in shaping their engagement with MOOC video lectures? The literature also showed that design considerations can influence positive and negative perceptions and evaluations of MOOCs. Therefore, this study will explore RQ2: What characteristics of MOOC video lectures most significantly impact learner affect, perceived cognition, and feelings of social connection?

Methods

Data Collection

This study uses secondary data. The starting point of data collection was the Class Central list (2023), The 250 Most Popular Online Courses of All Time (Shah, 2023). To focus on traditional higher education subjects and lecture styles, courses created by non-traditional education providers (e.g., DeepLearning.AI, Google, and IBM) were removed. To provide a variety of design styles from disparate disciplines, courses were classified into the commonly used head disciplines of academic study: applied science, natural science, formal science, social science, and humanities. The grouping draws from established disciplinary taxonomies (Becher & Trowler, 2001; Abbott, 2001) that recognize the delineation and flexibility of academic disciplines. Five courses under each head discipline were chosen for inclusion, meaning a total of 25 courses (10% of the original 250) were selected.

The secondary data for this study consists of learner-generated reviews, primarily student course evaluations, collected from the Class Central and Coursera platforms. These reviews reflect users' perceptions of MOOC video lectures (MVLs) and were selected based on a keyword search for "video" and "lecture," ensuring relevance to the study's focus. The reviews are ordered by the "Most Useful" rating system on these platforms, which ranks feedback based on user votes for helpfulness, though the specific criteria for "usefulness" are determined by the platform algorithms and may vary. This rating system introduces a potential for self-selection bias, as users who choose to rate or comment may have stronger positive or negative

experiences, potentially skewing the sample toward more engaged or dissatisfied learners. Additionally, there is no evidence that users were prompted with specific questions; the reviews appear to be unsolicited, voluntary responses, which may further contribute to variability in content and focus. Despite this, the large sample size (2,239 reviews) and diverse course selection help mitigate some bias by capturing a broad range of perspectives across disciplines.

Text Sampling

This study sought to collect 100 texts written about each course selected for inclusion. Texts were selected first from reviews hosted on Class Central and Coursera. The reviews are ordered by the “Most Useful.” A keyword search is performed using the tokens “video” and “lecture.” Reviews that feature these keywords are scanned to check the references to MVL germane to the course. Germane texts are copied and placed into a corpus. Saturation of collection is considered to have occurred once a total of 100 texts have been collected or no further reviews are found to include the initial keywords. The threshold of 100 reviews per course was chosen to balance depth of analysis with practical feasibility, ensuring sufficient data to capture diverse learner perspectives on MVLs. This decision aligns with qualitative research standards suggesting that thematic saturation often occurs after 60–100 responses (Guest et al., 2006), particularly in studies involving online reviews where user experiences may vary widely. The “Most Useful” ordering was prioritized because it reflects reviews deemed valuable by the learner community, likely providing detailed and relevant insights into MVLs, as opposed to chronological sampling, which might include less relevant feedback, or random sampling, which risks missing critical perspectives. However, this approach may introduce selection bias by favoring more extreme or eloquently written opinions, potentially overrepresenting strong positive or negative experiences. The keywords “video” and “lecture” were selected as the most direct and commonly used terms to identify MVL-related content, a method supported by prior research (Deng & Gao, 2023). However, this approach has a limitation: it may exclude valuable reviews using synonyms like “clip” or “presentation,” potentially narrowing the scope of captured perspectives. This constraint was accepted to maintain focus and feasibility in the data collection process. The final corpus used to generate qualitative data consists of texts from 2,239 individual reviews. Of the 25 courses, 15 included enough reviews that featured the keywords “video” and “lecture” to meet the saturation threshold of 100 texts. Of the remaining 10 courses, a range of 31–99 texts were obtained. The total number of tokens (words) in the corpus is 138,711, with tokens ranging from 1,167 to 8,962. The mean age of reviews in each course ranged from 1.14 to 4.28 years, with an overall mean age of 3.2 years. This study used a purposeful sampling strategy based on the platform’s “Most Useful” algorithm rather than a direct survey distribution to a known denominator of students. Therefore, a traditional response rate is not applicable. The sample represents a corpus of high-visibility feedback rather than a randomized cross-section of all enrollees.

Data Analysis

The texts are given identifiers made up of the letter “R” (for “Reviewer”), the course number (01–25), and the order in which they were selected (0–100). So, the identifier for the first reviewer of the first course selected is “R01/01,” and so on. Raw data were added into NVivo 14 for analysis. At the analysis stage, this study used a combined theoretical framework of

computer-aided qualitative data analysis software (CAQDAS) and flexible coding. Tracy (2020) says CAQDAS “not only eases the sorting and data management process, but also provides options that can lead to advanced interpretation” (p. 237). Tracy goes on to suggest that qualitative data analysis is appropriate when researchers want to capture online data, when there is a large amount of qualitative data to process, and when multiple participants or sites are involved in a study. For Deterding and Waters (2021), the use of qualitative data analysis software marks a paradigm shift away from a historical reliance on grounded theory (Glaser & Strauss, 1967), which they claim is not fit for analyzing large data sets, does not take into account the affordances of technological advances, and makes reanalysis of secondary data sets challenging. Instead, they claim, flexible coding is more appropriate to identify themes, instances, and examples of real-world phenomena in a non-linear and adaptive fashion to develop fresh categories and ideas from texts. This approach aligns with Guba and Lincoln’s (1985) call for systematic yet flexible methods in qualitative inquiry that prioritize trustworthiness through transparent, traceable analytic processes.

The coding process began with a deductive approach, using pre-established categories of cognition, affect, and social, which were directly informed by the CASTLE framework (Schneider et al., 2022) to align with the study’s theoretical lens. To ensure consistency during this deductive phase, strict boundary rules were applied to operationalize the CASTLE constructs. References related to mental effort, information processing, clarity, or understanding were coded as Cognition. Explicit emotional descriptors (e.g., “love,” “bored”) and statements regarding drive or persistence were coded as Affect. Finally, references to the instructor’s personhood, relationship building, or non-verbal signals (e.g., gaze, tone) were coded as Social. This rule-based approach prevented overlap before the inductive theme development began.

This was followed by an inductive phase to allow for the emergence of sub-themes and themes within these categories. In this paper, we use *themes* to refer to higher-order patterns within each CASTLE category, and *sub-themes* to refer to the more specific recurring ideas nested within those themes. In the first phase, coded excerpts within each category were reviewed for semantic similarity and clustered into candidate sub-themes. For example, texts expressing emotional responses (e.g., enjoyment, appreciation, frustration) were compared and grouped under Affect, while those discussing clarity, organization, and understanding were compared and grouped under Cognition. In the second phase, candidate sub-themes were refined through an iterative, constant-comparative process: sub-theme labels were merged when they captured overlapping meanings and split when excerpts reflected distinct ideas. In the third phase, the finalized sub-themes were examined to identify higher-order themes that represented recurring patterns across excerpts (e.g., positive versus negative affect; lecturer role/performance; production/design elements; interconnectedness with course resources) that represented recurring patterns within each CASTLE category (reported in the Findings section).

To enhance transparency, a short codebook is provided in Table 1, outlining the main categories, associated themes and sub-themes, definitions, and illustrative example quotes from the data. Inter coder reliability was assessed using Cohen’s Kappa, yielding an agreement score of .84, reflecting strong agreement.

Table 1*Short Codebook*

Category	Definition (CASTLE-informed)	Theme	Sub-themes	Example quote
Affect	Emotional responses to MVLs, including motivation, enjoyment, or frustration.	Positive affect	Enjoy/Fun/Love; Gratitude; Motivation	“I especially loved the animated videos” (R0566).
		Negative affect	Boredom; Unhappiness	“The professor was mind numbingly painful to listen to” (R2189).
Cognition	Processes related to understanding, retention, and cognitive engagement with MVLs (e.g., clarity, structure, organization).	Role of the lecturer	Personality; Pedagogic practice; Performance	“What a charismatic and passionate teacher he can transfer, through a single video, the intense interest he nurtures in the subject” (R0348).
		Design elements	Autonomy; Instructional design; Production	“The lectures are clear, concise, and engaging, making the material accessible to learners of all levels” (R0246).
		Inter-connectedness	Resources; Assessment alignment	“Great set of slides, readings and the video lectures. Used many different modalities to illustrate points” (R2268).
Social	Perceptions of social presence/connection through MVLs (e.g., relational cues, interpersonal warmth, co-presence, non-verbal signals).	Teacher–student connection	Co-presence/shared space	“You feel like you were in a real lecture room with the lecturer” (R05100).
		Personality	Warmth/enthusiasm/humor	“Delivers the lectures with such passion and enthusiasm” (R2172).
		Physical cues	Speech/embodied cues	“Speaks to the audience, not the camera” (R1221).
		Absence	Missing social cues	“They don’t allow you to feel any connection with the professor” (R0528).

Trustworthiness

To support the trustworthiness of the qualitative analysis, we drew on Guba and Lincoln's (1985) criteria of credibility, transferability, dependability, and confirmability. Table 2 summarizes the main strategies implemented for each criterion in this study.

Table 2

Four Criteria for Trustworthiness

Criteria	Strategies Implemented
Credibility	CASTLE-aligned boundary rules to guide deductive coding of reviews into cognition, affect, and social categories. Primary coding by the first author, followed by an independent inter-rater check on a sample of reviews using the finalized codebook, consistent with process-based guidance on intercoder reliability (Cofie et al., 2022). Cohen's kappa = .84.
Transferability	Purposeful sampling of 25 MOOCs across five head disciplines to capture diverse MVL designs and learner perspectives. Thick description of the corpus and context (platforms, "Most Useful" ordering, keyword filters, number of reviews and tokens, review age range).
Dependability	Structured multi-phase analytic process (deductive categorization → inductive development of sub-themes and themes). Consistent use of stable identifiers (R + course number + selection order) and NVivo 14 project organization to track coded excerpts.
Confirmability	Reporting themes with illustrative quotations and identifiers to allow readers to trace interpretations back to specific reviews. Use of an explicit CASTLE-informed coding frame and codebook to constrain categorization and reduce individual interpretive bias.

These strategies were used to enhance the rigor and transparency of the qualitative analysis and to align the study with established criteria for trustworthiness in naturalistic inquiry. We next present the findings addressing RQ1 and RQ2.

Findings

RQ1. Learner perceptions of affective, cognitive, and social cues in MVLs

To address RQ1, we report learners' perceptions of affective, cognitive, and social cues in MOOC video lectures (MVLs) as expressed in learner reviews. We present the findings by CASTLE-aligned categories (affect, cognition, social), summarizing the principal themes and illustrative examples that recurred across the corpus.

Affective Cues

Positive affect related to MVLs was coded in 502 reviews across 25 courses, with three themes emerging: love, gratitude, and motivation. Negative affect was noted in 76 reviews across 19 courses, with two themes: boredom and unhappiness.

Positive Affect

The theme of *love* was coded in 225 reviews of 25 courses. Learners expressed enjoy/fun/love through comments like R12/31: “The lecturer made the course fun” and R05/66: “I especially loved the animated videos.” The stemmed word *thank* was returned 489 times and was the most frequent word relating to affect found. The theme of *gratitude* was coded in 97 reviews of 20 courses. Gratitude was expressed to lecturers (e.g., R18/67: “I have learned so much. Professor Manson is simply amazing. Thank you”), to the production team (e.g., R21/44: “Thank all the team and lecturers, who put this course together, for their hard work!”), and to institutions (e.g., R03/57: “Special thanks to Yale and Coursera for making this accessible to the masses”). The theme of motivation was identified in 180 reviews from 20 courses. Learners expressed it in statements like R12/84: “I ended up listening to the lectures while eating all three meals,” and R24/20: “inspired me to apply to university.”

Negative Affect

Boredom surfaced in 57 reviews across 17 courses. Learners noted it with comments like R21/89: “the professor was mind numbingly painful to listen to,” and R25/11: “Background is boring.” *Unhappiness* was coded in 19 reviews from 9 courses. It appeared in remarks like R07/04: “The lectures were so steeped in SJW tropes,” and R20/16: “diminished by the professor.”

Cognitive Cues

The stemmed word *learning* was returned 937 times while *understand* returned 597 times, or the fourth and sixth most frequent in the corpus, respectively. The largest number of coded texts related to cognition with 2,186 references across all 25 courses, with 1,442 reflecting positive perceptions and 744 negatives. These references were themed by role of the lecturer, design elements, and inter-connectedness.

Role of the Lecturer

There were 485 positive and 101 negative mentions of the *role of the lecturer* in relation to cognition. One sub-theme was the facilitating role of the lecturer’s *personality*, referenced positively 196 times across 22 of the courses and attributed to the lecturer’s role as providing charismatic leadership, being a cheerleader for a subject, embodying a subject matter expert, and providing humor. R03/48 wrote of the lecturer “What a charismatic and passionate teacher; he can transfer, through a single video, the intense interest he nurtures in” the subject. R02/13 wrote that the lecturer’s “enthusiasm for the subject is evident throughout the course, making it enjoyable to learn.” R21/10 said the lecturer “lends his own intellectual brand of associations to certain of the more complex ideas, thus rendering them accessible to learners who are new.” R02/69 wrote the lecturer’s “fun way of explaining things both in his videos and the book will help you learn things in a simple way.”

Another subtheme was the lecturers' *pedagogic practice*, stated in 180 reviews covering 24 courses, with giving *clear explanations* (89), *introducing content at the appropriate level of cognitive load* (64), and *using examples* (23) emerging within the subtheme. R02/29 wrote "the instructor uses simple language to explain complex concepts, making it easy for anyone to understand," R08/80 wrote that the lecturer "broke everything down to the barest minimum for us to understand," and R08/28's "The lecturer was providing the right examples, which helped me to understand concepts clearly." Learners also wrote negatively of *pedagogic practice* in 28 references for 11 courses. For R03/16 "no specific and concrete topics were presented [or] explained" while R15/08 noted challenges if learners were not "Up-to-date on all the latest and great math jargon" and R15/13 stated lectures were too "high-level."

Lecturing as *performance* facilitating cognition was coded in 109 references to 22 courses. R15/67 wrote the lecturer "has a good speaking and teaching style which keeps me interested" and for R05/29 the tone in the lecturer's performance was noteworthy because "He is very soft spoken and maintains composure" which helps learners "fully understand their experiences." The negative reviews of *performance* were coded in 74 references to 21 courses. R03/10 wrote that their lecturer "was not very engaging and did not really provide emphasis on key concepts to make it stick" and R14/58 the lecturer "was constantly looking sideways to read the text. It was very distracting for me." R05/75 noticed "occasional "hum and haw" episodes which sound very irritating in an online course."

Design Elements

There were 733 references to 25 courses coded as relating positively to *design elements* and *cognition*. These were made up of three sub-categories: *autonomy* (87), *instructional design (positive)* (288), and *production (positive)* (358). There were 508 negative references made up of *production (negative)* (248), and *instructional design (negative)* (260).

The stemmed keyword *online* appears in 144 references to all 25 courses, while the stemmed keyword *download* appears 16 times. Reviewers that discussed *autonomy* spoke of self-determination and control over their learning. R07/21 wrote "Loved the freedom to explore the lectures at times where it fit in my schedule [...] Learned a lot of information" and R21/46 said, "the ability to learn online at my own pace over the week fitted in well with working at home." R03/65 wrote: "I definitely found it okay to increase the video speed to 1.5X, as the dialogue is very clear and paced to be easily understood by all," and R18/35 stated "I will be definitely coming back, watching the videos for a better understanding of the material."

Reviewers discussed the instructional design practices that promoted learning. Reviewers talked about the value of MVLs that are clear, concise, easy or simple, engaging, and included examples to explain ideas. R02/46 writes "The lectures are clear, concise, and engaging, making the material accessible to learners of all levels," while R04/38 states, "Videos were clear, straightforward and easy to follow and understand" and R14/26 adds "All the videos were clear and easy to follow and understand." Negative reviews included things like R07/29's "Could not follow lessons. Information in the videos is very scattered" and R11/11's "most of the videos were too complex to understand without prior knowledge on the matter."

Reviews coded as relating to *production* can be broken into three sub-themes: *length* (positive 121 / negative 91), *media* (positive 104 / negative 56), and *quality* (positive 133 / negative 99). There was support for shorter lectures, for example R02/94 wrote “The video has divided into the small part, normally 10-15 mins, makes it easy to learn” and criticism of longer artifacts, for example R13/08 wrote that from a “pedagogical angle [...] you can’t do 27-minutes video when we know that the average focus of a student is lower than that.” Some learners suggested ideal times: “max 5 minutes” (R06/58), “max 7 minutes” (R22/10), and “no longer than 10 minutes” (R25/67). Learners called out positive uses of multimedia production: R04/60 felt lectures were “easy to understand” when they “have a picture and some detail of the lesson in the video to explain more things” and R05/39 appreciated “images and bullet points as support.” Reviewers also called out perceived negatives in multimedia production choices: R03/14 noted that text media was “too wordy and/or provide a reference guide on what was covered in the entire lecture” and R05/04 stated “obnoxious sound effects to drown out the speaker.”

When positive, commentary on *quality* tended to be broad: R02/29 offered “Videos are very good quality,” and R15/16 “The video production is really good.” However, negative comments tended to include specifics. R07/02 noted “Titles projected within the video are often misaligned; some have animations, others do not, and this inconsistency undercuts the value of the content” and R14/11 observed “The video content production came across as very amateur, lines of flubbed dialogue left in, and overall just came across as unprofessional.” R07/11 noted “The videos failed to utilize the potential of motion pictures and instead relied on teleprompter reading.”

Inter-connectedness

The stemmed word *course* was the most frequently returned, with 3,013 tokens available. This compares with *lecture* at 1,824 and *video* at 1,333. The stemmed word *assignment* appeared in 201 references, *test* appeared in 128 references, *quiz* appeared in 119 references, and *assessment* in 36. Interconnection with course materials, resources, and assessments that affected learning was mentioned as a positive in 224 reviews covering 25 courses and as a negative 136 times covering 23 courses. Reviewers wrote about connections to resources as a positive, for example R22/68 wrote “Great set of slides, readings and the video lectures. Used many different modalities to illustrate points,” or as a negative, for example R09/93 felt “There are almost no actual readings, and the videos are helpful but don’t tell you everything you need to know.”

The inter-connectedness between assessment and MVLs was unusual in that the frequency of negative references (95) was higher than positive (86) references. Learners noted inconsistencies, for example R16/02: “I felt I was really developing a deeper understanding. BUT then the exams at the end of each lecture consistently required” knowledge outside that presented in MVLs. R18/05 wrote “Often, it felt like the questions were on information that the teacher said almost in passing.” Conversely, learners also had a favorable view of knowledge measures and appreciated them when perceived as useful: “Very nice lectures and practice quizzes” (R23/17) and an “approach of learning were you watch lectures, and then review material with quiz” (R02/66) was appreciated.

Social Cues

Social elements in MVLs yielded 608 references across 25 courses, grouped into *teacher–student connection*, *personality*, *physical cues*, and *absence*.

Teacher–Student Connection

There were 300 texts, referring to 25 courses, coded to reflect the phenomenon of the learners perceiving a social relationship. 198 used formal titles (*lecturer*, *instructor*, *teacher*, *professor*), signaling a traditional, hierarchical view of the relationship. Meanwhile, 49 learners used lecturers' first names, recognizing instructors as approachable social actors. Learners described a "good and interesting lecturer" (R03/03), "a very good teacher" (R04/31), and "Peter" giving "enthraling lectures" (R21/71). Additionally, 53 references highlighted a sense of shared instructional space, as in: "you feel like you were in a real lecture room [with the lecturer]" (R05/100) and lectures were "the same [...] as we would have received sitting in a classroom in New Haven [the home of Yale University]" (R24/42).

Personality

Learners (214) noticed when they were able to discern *personality* traits in lecturers. R21/72 noticed the lecturer "delivers the lectures with such passion and enthusiasm." Learners also recognized social cues in the humorous behaviors of lecturers. For instance, R21/30's review included "The lecturer was excellent and showed a great love for the subject with the occasional unexpected injections of humour." Other aspects of a lecturer's "personality came through" (R18/76) in MVLs like them being "kind" (R08/57), "patient" (R04/28), or "warm" (R02/35).

Physical Cues

Direct references to *physical cues* were coded in 59 reviews of 18 courses. Of these, social cues in *speech* were noted in 43 reviews when the lecturer "talks to you" (R02/72) and "speaks to the audience, not the camera" (R12/21). A small number, 16, reported *embodied social cues*, including a positive report of the lecture's "accompanying smile" (R01/34) and a negative review of a lecturer who "always folds their hands in front of their waist" (R03/38).

Absence

There were 35 reviewers of 9 courses that noticed negative perceptions when *social cues* were *absent* because they "don't allow you to feel any connection with the professor" (R05/28) or the lecturer "was just reading the content out of a script rather than trying to convey or interact with the students in any sense" (R14/47).

RQ2. MVL characteristics most significantly impacting learner affect, perceived cognition, and feelings of social connection

RQ2 asks which MVL characteristics most significantly impact learner perceptions across the three CASTLE dimensions. Based on the learner perceptions reported in RQ1, we synthesize the findings here to highlight the specific characteristics that shaped affect, cognition, and social connection.

Role of the Lecturer

The characteristics of the lecturer, specifically their personality and delivery style, emerged as the most significant influence on learner perceptions across all three dimensions. The high frequency of love and motivation codes (affect) highlights how massive virtual learning environments often create enjoyable experiences, deepening emotional investment. This emotional engagement was tied to engaging content or a lecturer's charisma, making learning memorable. In a broader analysis, these positive affective responses fueled enthusiasm, promoted active participation (cognition), and often stemmed from the lecturer's inspiring presence (social).

Conversely, characteristics such as reading from a script or lack of eye contact were central to reports of boredom and unhappiness. The presence of boredom suggests some MVLs fail to stimulate, risking disengagement. Boredom points to a lack of dynamic content or delivery, weakening emotional and cognitive investment. Viewed conceptually, it diminishes interest (affect), reduces retention (cognition), and can make the delivery feel detached (social). This theme suggests that learners are highly sensitive to the lecturer's personal characteristics, which play a significant role in shaping their perception of the MVLs.

Design and Production

Production characteristics significantly impacted how learners processed content (cognition) and felt about the course (affect). Positive perceptions were driven by characteristics that supported autonomy and reduced cognitive load, such as short video length, clear segmentation, and the use of supporting visuals. The prevalence of motivation indicates MVLs often drive persistence and real-world action, showing strong learner engagement.

Negative production characteristics, such as poor audio or "flubbed" lines, were not just cognitive distractions but also affective irritants. Unhappiness, though less frequent, carried weight, signaling dissatisfaction. It stemmed from unmet expectations, such as perceived bias or disrespect. In an evaluative sense, it generates negative emotions (affect), distances learners (social), and may render content irrelevant (cognition). This theme indicates that physical and production cues are a noticeable and impactful aspect of MVLs.

Interconnectedness and Social Presence

The final set of characteristics concerned the degree of connection, both interpersonal and structural. Interpersonal connection was driven by social cues that fostered a sense of co-presence. These patterns suggest that social presence is important for engagement: some learners value authority and structure, while others respond to warmth and relatability. The sense of co-

presence and authenticity, evoked by both formal and informal cues, supports motivation and belonging.

Structurally, the connectedness of MVLs to other course elements (assessments and resources) was important. Gratitude suggests learners deeply appreciate the effort invested in creating meaningful MVLs, reflecting an emotional connection to the learning experience. Gratitude here indicates a recognition of value, accessible content, inspiring teaching, or high-quality production, which fosters a positive emotional response. Within the CASTLE framework, gratitude ties to affect by boosting motivation, to social presence as learners thank lecturers for fostering connection, and to cognition as appreciation often links to clear, useful content. Conversely, the absence of cues or misalignment with assessment suggests that learners actively notice and are negatively affected by a lack of engagement or interactivity, which directly weakens social presence and can lead to alienation.

Discussion

This study illuminates how learners perceive affect, cognition, and social cues in MOOC video lectures (MVLs), particularly emphasizing the lecturer's role and learners' streaming-like consumption behaviors. These findings are contextualized within existing literature on MOOCs, highlighting both alignment and divergence with prior work.

The Lecturer as a Central Figure

Consistent with existing research, this study underscores the lecturer's pivotal role in shaping learners' perceptions of MVLs. Positive learner reviews often praised lecturers for their passion, enthusiasm, and charisma, echoing findings from Wei et al. (2022), who noted that intrinsic motivation and instructor presence significantly influence learners' perceived outcomes. Similarly, Deng and Gao (2023) emphasized that lecturers who demonstrate organization, clarity, and accessibility contribute to favorable learner perceptions.

However, this study adds nuance by highlighting the dual role of lecturers as both educators and performers. While prior research has largely focused on cognitive aspects like instructional clarity (Wei et al., 2022) or technological features like media-rich design (Deng & Gao, 2023), our findings suggest that affective elements, such as humor, warmth, and enthusiasm, are equally critical. For instance, learners described lecturers as "cheerleaders" or "charismatic leaders," attributes that transformed the educational experience into something akin to entertainment. This aligns with Atapattu and Falkner (2018), who found that narrative and conversational discourse enhances learner engagement, but our study extends this by illustrating how these qualities evoke emotional investment, often expressed as gratitude or loyalty.

Conversely, when lecturers failed to engage dynamically, through monotone delivery or excessive dependence on scripts, learners reported negative emotions such as boredom or frustration. This observation supports Fuller et al. (2020), who highlighted that less interactive and overly formal approaches can erode the relational aspect of learning, limiting engagement.

Streaming-Like Consumption

One of the unique insights from this study is the framing of MVLs as part of a “want-to-learn” streaming culture, where learners approach educational content with expectations akin to entertainment. This behavior mirrors findings by Deng and Gao (2023), who observed that learners prioritize shorter, well-produced videos to reduce fatigue and maintain interest, much like selecting episodes in a binge-worthy series.

However, our findings suggest that learners’ motivation extends beyond mere consumption; many expressed using MVLs to inspire life-changing decisions, such as applying to university. This deeper engagement contrasts with Perez-Navarro and Conesa’s (2021) work, which focused on satisfaction with technical features and video formats but did not explore the transformative potential of MVLs. By framing MVLs as a blend of entertainment and education, this study bridges the gap between the instrumental and aspirational aspects of MOOC learning experiences. This consumption pattern closely mirrors the “Netflix effect” or binge-watching behaviors identified in media studies (Matrix, 2014), where viewing is driven by a desire for narrative continuity and emotional connection as much as content acquisition. Just as binge-watchers sustain attention through “parasocial” bonds with fictional characters, MOOC learners appear to sustain cognitive effort through similar bonds with the “performer” lecturer.

Cognition and Instructional Effectiveness

Cognitively, our findings align with Wei et al. (2022) and Deng and Gao (2023), who highlighted the importance of clarity, conciseness, and scaffolding in instructional design. Learners in our study frequently praised clear explanations, incremental difficulty, and practical examples. These elements were particularly valued when integrated with high production quality, a finding consistent with Deng et al. (2017), who emphasized that well-edited, visually engaging videos enhance understanding.

However, this study also reveals tension points absent from much of the prior literature. While instructional clarity was lauded, scattered or overly complex content drew sharp criticism, suggesting a need for greater alignment between video lectures and supporting materials. Learners in our study echoed concerns from Fuller et al. (2020) regarding the disconnection between MVLs and assessments, which sometimes led to frustration and diminished learning outcomes.

Social Cues and Connection

The study reaffirms the importance of social presence in MOOC learning, particularly through lecturers’ use of non-verbal cues, conversational tone, and humor. Deng and Gao (2023) similarly highlighted the role of embodied social cues in creating a sense of connection, but our findings extend this by showing how learners actively interpret these cues as indicators of the lecturer’s authenticity and commitment. Positive perceptions of warmth, humor, and approachability were frequently tied to learners feeling part of a shared learning experience, reflecting the principles of connectivist pedagogy (Fuller et al., 2020).

Yet, the absence of social cues, such as lecturers reading from scripts or lacking eye contact, was perceived as alienating, reinforcing findings from prior MOOC research that teacher presence and engaging instructional practices are central to learner engagement, cautioning against impersonal, overly scripted delivery (Deng et al., 2017). This reinforces the need for MOOCs to balance the efficiency of scripted content with the relational dynamics that foster a sense of belonging.

Learning from the Negative: Anti-Patterns for Design

While positive reviews highlight effective practices, the negative reviews offer a critical “anti-pattern” for instructional design. The recurrence of the codes *boredom* and *unhappiness* suggests that static visual delivery (e.g., “teleprompter reading”) and poor audio quality are not merely neutral absences of good design, but active detractors that sever the social connection. Designers should prioritize dynamic framing and authentic delivery over high-budget polish, as learners appear to penalize “amateur” technical flaws and “robotic” performance more heavily than simple visual presentation. Practically, this implies that investment in lecturer training (specifically in on-camera delivery) may yield higher engagement returns than investment in post-production graphics.

Practical Implications

These findings suggest that MOOC practitioners should reimagine lecturers as both educators and performers. Training programs for lecturers could incorporate principles of narrative storytelling and audience engagement, drawing from both educational and media production fields. Additionally, MOOC design should cater to learners’ streaming-like preferences by emphasizing shorter, visually appealing videos that integrate social and cognitive cues effectively. Finally, enhancing the interconnection between MVLs, assessments, and supplementary resources is essential to ensure coherence and continuity in learning.

Theoretical Contributions

This study contributes to the literature by contextualizing the CASTLE (Cognition, Affect, Social-Teacher, Learner-Environment) framework within the evolving landscape of MOOC consumption. It highlights how lecturers’ affective and social roles intersect with learners’ motivations to create an educational experience that feels both personalized and aspirational. Furthermore, by framing MVLs as a hybrid of education and entertainment, this study opens new avenues for exploring how media consumption behaviors influence digital learning.

Limitations and Future Directions

This study relies on unsolicited learner reviews, which introduces several forms of sampling bias. Reviews were drawn from Class Central and Coursera and ordered by platform “Most Useful” rankings, which may privilege unusually detailed or extreme perspectives and may disproportionately surface praise for charismatic, high-performance lecturers. In addition, the reviews appear voluntary and not prompted by a standardized set of questions, which may

increase variability in what learners choose to comment on. Finally, the corpus was assembled using keyword searches for “video” and “lecture,” which may exclude relevant reviews that refer to MVLs using different terms (e.g., “clips” or “presentations”), narrowing the range of captured perspectives. Because the dataset reflects a high-visibility corpus of feedback rather than a randomized cross-section of all enrollees, a conventional response rate is not applicable.

Conclusion

This study reveals the critical role of lecturers in shaping learners’ perceptions of MVLs and the emerging trend of streaming-like consumption patterns in MOOCs. By framing MVLs as both educational and entertaining, the findings suggest that lecturers must balance instructional clarity with affective and social presence to foster meaningful engagement. Practical recommendations include training lecturers as educator-performers, designing shorter, visually engaging videos, and enhancing the integration of MVLs with broader course materials.

The study extends the CASTLE framework by illustrating the intersection of cognitive, affective, and social dimensions in digital learning environments. It highlights the need for future research to incorporate diverse methodologies, including analytics-based measures, to validate and extend these findings across cultural and demographic contexts. As MOOCs continue to evolve, understanding how learners interact with MVLs will be critical to creating effective, learner-centered digital education experiences.

Declarations

Ethics Statement

This study was approved by the author’s affiliated institution under IRB 24427.

Conflicts of Interest

The author(s) declare no conflicts of interest.

Funding Statement

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AI Use Statement

Generative artificial intelligence (AI) was used in the preparation of this manuscript for style refinement, proofreading and grammar checks, and reference list formatting. The AI tool was not used to generate, analyze, or interpret research data, nor to create original scholarly content. All content was reviewed, verified, and approved by the author, who takes full responsibility for the accuracy and integrity of the work.

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Empowering the Next Generation: A Holistic Self-Care Course for Cultivating Resilience in Undergraduate Students

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Abstract

College students experience stressors that can impact grades, relationships, and health. These challenges can arise in online, hybrid, and in-person learning environments, and are often compounded by time pressures, social isolation, and the challenge of balancing responsibilities across work, school, family, and friendships. When students participate in structured education in self-care techniques, they can build resilience and effective coping strategies. An undergraduate asynchronous, online elective in holistic self-care was developed to promote student resilience and stress management. After receiving positive feedback over several terms, a concurrent mixed methods pre-post study was embedded in this course to evaluate the impact on student stress and resilience, as measured by the Perceived Stress Scale (PSS) and the 10-item Connor-Davidson Resilience Scale (CD-RISC-10). Open-ended questions in the post-course evaluations captured students' perspectives on the experience. The findings revealed that students who engaged in holistic self-care practices taught in the course reported lower stress, greater resilience, and an appreciation of strategies that support their overall well-being.

Keywords: College students, academic pressures, holistic self-care, stress management, resilience, mental health

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College students are beginning the next phase of their lives, one that is filled with new experiences and opportunities. This is an exciting and inspiring time of personal growth, but undergraduate students often face significant stress as they adjust to the new environment and the rigors of academic life, whether they are learning online, in hybrid formats, or on campus (Barbayannis et al., 2022). In addition to academic pressures, many college students are adapting to living away from family and friends for the first time (Kerr & Claybourn, 2023). They may also experience stress from financial obligations, interpersonal relationships, and post-college employment uncertainty (Dong et al., 2024). These stressors are compounded by social media, societal unrest, and anxiety about personal health and campus safety (Campbell et al., 2022).

There is convincing evidence that college students are experiencing more frequent and more severe mental health problems (Healthy Minds Network, 2023). Despite the high incidence of psychological distress and the clear need for support, college students often report feeling disconnected, potentially leading them to unhealthy coping mechanisms, such as substance use, high-risk behaviors, and social isolation and withdrawal (Dong et al., 2024; Nelson et al., 2021). These findings underscore the importance of formal initiatives to bolster student well-being. The aim of this study was to examine the impact of an online ten-week undergraduate holistic self-care course on students' perceived stress and resilience.

Background and Significance

Stress of Undergraduate Students

"Stress" is the body's natural response to any real or perceived pressure that threatens the homeostatic state (Schneiderman et al., 2005). Threats, also known as "stressors", can be physical, mental, or emotional in nature and cause a cascade of complex systemic changes. While the body is adept at overcoming occasional or short-term stressors, layered or ongoing stress can produce or worsen disease states, which includes mental health disorders.

Stressors pervade the college experience. Though each student has unique causes of and responses to stressors (Reddy et al., 2018), 87% of Gen Z (ages 18-23) college students shared that education was a significant source of stress (American Psychological Association [APA], 2020). Notably, there are unique pressures faced by today's college students, including social media stressors, such as cyberbullying (Martínez-Monteagudo et al., 2020), the risk of behavioral addiction related to excessive smart device use (Li & Liu, 2021), and known and yet unidentified enduring effects of the COVID-19 pandemic (Brown et al., 2024). As high levels of stress during college may serve as a predictor of future mental health disorders (Barbayannis et al., 2022) and lower academic attainment (Kötter et al., 2017), educators should consider the following themes and findings that have emerged in the literature, as they are notable across undergraduate student demographics.

Undergraduates and Academic Stress

Academic stress, or a "psychological state resulting from continuous social and self-imposed pressure in a school environment that depletes the student's psychological reserves" (Zhang et al., 2022, para. 3), is especially heightened during the first years of study (Trigueros et al., 2020). Academic stress is layered (Mofatteh, 2021) and can stem from external sources, including teacher-student dynamics (Trigueros et al., 2020); unexpected difficulties, such as technical issues (Islam & Rabbi, 2024); and peer and social pressures as students adjust to new cultures and communities. Academic stress is also shaped by internal factors, including feelings

of inadequacy, fear of failure, and personality traits such as dispositional optimism-pessimism (Chang, 1998). Outcomes such as homesickness, perceived discrimination, hate, or rejection may be more prevalent in international students (Li & Liu, 2021).

Academic stress can dominate other stressors, and the effects may lead to poorer mental and physical health outcomes (Barbayannis et al., 2022). High levels of academic stress have been associated with risky behaviors, such as increased substance intake (Nelson et al., 2021); including the use of “study drugs” (Valimohamed, 2019); risky sexual behaviors (Mehra et al., 2014); and neglect of other physical needs, such as sleep and proper nutrition (Pascoe et al., 2019). Across demographics (age, gender, race/ethnicity, academic year), a study of college students residing in the United States found an association between higher levels of perceived academic stress and worse overall mental well-being (Barbayannis et al., 2022). Untreated poor mental health can lead to distress and suicidal thoughts among students, negatively influence a student’s quality of life, affect relationships, and reduce academic performance and integrity (Mofatteh et al., 2021). The phenomenon may be cyclical as higher academic stress leads to worsened mental well-being, which has been shown to exacerbate academic stress.

Previous efforts to address academic stress among undergraduate students have often centered on providing information about stressors and introducing general stress management techniques. For instance, Hintz et al. (2014) demonstrated that targeted online training modules in stress management led to reductions in perceived stress, anxiety, and depression. Recognizing that knowledge alone may not be sufficient, Conley et al. (2015) emphasized the value of combining psychoeducational content with skills-based training and opportunities for practice to enhance students’ abilities to manage their mental health effectively.

A particularly compelling example is *The Power of Nursing* (PON), a course grounded in the Healer’s Art framework, which fosters self-care, resilience, and professional identity formation through experiential and reflective learning (Snow et al., 2024). Delivered in both in-person and online formats, PON promotes holistic values such as authenticity, empathy, and self-awareness, and has been associated with improved well-being and a stronger sense of connection among students (Snow et al., 2024). These interventions highlight the potential of structured, skills-based educational programs to reduce academic stress, enhance psychological flexibility, and promote resilience.

Impact of COVID-19 on Undergraduate Students

Current undergraduate students continue to face unique stressors related to learning in a post-pandemic era. The SARS-CoV-2 (COVID-19) pandemic impacted life ubiquitously (Onyeaka et al., 2021). Early data revealed that over a billion global learners were affected by abrupt school closures. For some students, stress was exacerbated by the additional burden of tackling dormitory housing displacement (Jackson & Johnson, 2020). Beyond academic, sports, and social disruptions (Serafini et al., 2020), formal institution closure orders brought about food insecurity (Onyeaka et al., 2021); abandoned or altered graduation ceremonies (Alter, 2020; Blythe et al., 2020); and lost internships and job opportunities (Lee et al., 2021). Since 2020, cohorts of learners faced financial uncertainty (Lee et al., 2021) and many were additionally impacted by the death of loved ones (ElTohamy et al., 2022).

College students continue to report remarkable increases in overall stress (Barbayannis et al., 2022), mental health diagnoses (Chirikov et al., 2020), and feelings of loneliness (Lee et al.,

2021), complicating academic performance since the pandemic (Hu et al., 2022; Zhang et al., 2025). Marginalized students, including low-income learners, Persons of Color, and those who identify as non-binary or transgender, were impacted to a greater degree across many measures, including financial access to college (Causey et al., 2021); academic stress (Barbayannis et al., 2022); and rates of depression and anxiety (Chirikov et al., 2020). Yet, hope remains.

Cultivating Student Resilience for College and Beyond

Resilience is “the process and outcome of successfully adapting to difficult or challenging life experiences, especially through mental, emotional, and behavioral flexibility and adjustment to external and internal demands” (American Psychological Association, 2018, para. 1). This process harnesses inner resources to counteract the impact of stressors for improved adaptation to adversity (Fullerton et al., 2021). Resilience is positively correlated with self-efficacy, effective coping skills, and psychological well-being, enabling people to bounce back and even thrive in challenging situations (Rees, 2015).

The college environment exposes students to intensifying academic demands, financial responsibilities, and social pressures as they navigate the novelty and stress of independent living. Higher levels of student resilience, however, are positively correlated with adaptability, goal attainment, subjective well-being, and stronger academic performance (Li et al., 2024). Resilience helps students to overcome academic setbacks, foster a growth mindset, and persevere when challenged (Fullerton et al., 2021). Resilience is also associated with self-regulation, a trait that is essential to maintaining motivation, setting realistic goals, and approaching learning strategically for greater academic success (Li et al., 2024).

Structured learning opportunities focused on self-care and resilience-building can foster coping skills and help students to effectively manage the stressors they confront in undergraduate education (Grimaldi, 2023). Consequently, universities are urged to promote student resilience and adaptability by developing programs that build psychological capacities, teach relaxation techniques, and share resources (Li et al., 2024). Higher education programs that cultivate resilience and stress management prepare the next generation with lifelong skills to address the complexities and challenges of life after graduation.

Holistic Self-Care Course: Course Description

Holistic Self-Care is a ten-week course that was initially developed for nursing students and later made available to all undergraduate students as an elective. This is the course in which the study took place. The fully asynchronous online format was designed to help reduce student stress and promote overall well-being. The course integrates didactic and experiential components to support a holistic, balanced student life. Its structure intentionally combines evidence-based learning with applied self-care practices to cultivate self-efficacy and strengthen the interconnected dimensions of mind, body, and spirit.

Didactic learning is beneficial for increasing knowledge and awareness; however, experiential learning is essential when affecting health behaviors (Villarroel et al., 2020). In experiential learning, students learn through “doing” and reflection, which can increase student autonomy and responsibility (Villarroel et al., 2020). The benefits of experiential learning include connecting content theory (didactic) and the experience (Villarroel et al., 2020). In this

case, the experience was holistic practice. In addition, experiential learning allows students to be personally involved in their learning process (Villarroel et al., 2020). Overall, it was intended that students would obtain a holistic self-care “toolkit” to use beyond university life.

There were typically multiple sections of the course offered each quarter, with approximately 25 students in each section. The course was organized into five modules, each two weeks in length, offered in a fully online format. Module topics included stress management, mindfulness and meditation, nutrition for self-care, spirituality and movement, self-efficacy, and a positive mindset. Each module consisted of a discussion board, an experiential journal, and a quiz. The instructors who taught the course were skilled in holistic practices, such as mindfulness, meditation, yoga, aromatherapy, and other complementary therapies. Various pedagogical approaches were utilized in the course to engage and support all learners. Modules focused on the broader topic of stress, and additional techniques were introduced throughout the course, such as aromatherapy. Students shared summaries from the pre-course self-assessments of perceived stress, resilience, and well-being in the first discussion board regardless of their participation in the study. A major experiential project required students to choose a holistic self-care practice, research the benefits, practice it, and share an in-depth reflection. They reflected on how their choice of, and length of practice affected them overall—mind, body, and spirit—including their overall stress levels. Students were given the autonomy to creatively present their project via a formal research paper, visual presentation with voiceover, or other media.

Theoretical Framework and Research Questions

To investigate the impact of this Holistic Self-Care course, a concurrent mixed methods study, informed by the Integrative Student Growth Model (ISGM), was designed. This model emphasizes the critical role of holism and self-care for student success. Holism in higher education is “the process of synergizing the totality of the student experience that is inclusive of mind, body, spirit, environment, and culture into both the learning environment and the teaching-learning process, to promote optimum academic performance, professional growth, and personal wellness” (Patestos et al., 2019, p. 88). With a focus on the whole student, this theoretical framework addresses the physical, emotional, social, and intellectual aspects of a student’s life.

The ISGM highlights the potential for student growth through practices that help students manage stress, maintain mental health, and build resilience (Patestos et al., 2019). This supportive learning environment encourages both academic and personal growth in a way that is holistic, inclusive, and interconnected (Kean University, 2018). The goal of the ISGM is to inspire students to thrive and adapt in a constantly changing world so they are able to “conquer the rigors of academic life while maintaining a healthy dose of self-care and professional growth” (Patestos et al., 2019, p. 88). Although literature on the ISGM is still emerging, its components align with well-established theoretical foundations that foster student stress reduction and holistic development, particularly in online and remote learning environments.

Positioned as the central framework for this study, the ISGM is illuminated by complementary theories that emphasize modeling, developmental growth, and connection. Bandura’s Social Learning Theory supports the ISGM’s focus on modeling and self-efficacy, suggesting that new behaviors are more likely to be learned and sustained when demonstrated by others and reinforced in supportive environments (Bandura, 1977; Parcel & Baranowski, 1981). Similarly, Benner’s Novice to Expert Theory aligns with the ISGM’s developmental perspective

by describing how learners progress from basic awareness to more integrated mastery through reflection, experience, and guided mentorship (Benner, 1982; Williams, 2023). As self-care is a learned competency, these perspectives reinforce the ISGM's emphasis on experiential learning and the gradual internalization of wellness practices over time.

Additionally, the Interactivity/Community-Process Model complements the ISGM by underscoring how connection, engagement, and community are critical to learning in online settings (Lear et al., 2010). This alignment extends the ISGM's holistic principles into virtual environments where distance, isolation, and stress can otherwise hinder student well-being. ISGM-guided strategies, such as faculty modeling, value-centered interaction, and intentional community-building, mirror the processes identified in the Interactivity/Community-Process Model and highlight the importance of active engagement and meaningful relationships in supporting growth.

Ultimately, the ISGM serves as an integrative framework that draws on established learning theories to support student development. In online learning environments where students often encounter increased stress, reduced interaction, and limited opportunities for personal connection, the ISGM's emphasis on modeling, engagement, and wellness becomes especially relevant. When instructors cultivate environments that promote timely and meaningful interaction, alongside personal growth, students experience greater engagement, motivation, and satisfaction (Martin & Bolliger, 2018; Dixon, 2015). In this way, the ISGM is not only a conceptual model but also a practical guide for strengthening self-care competencies in online learners. The Holistic Self-Care course embodies these principles in a structured approach and builds on this work to promote both academic success and personal well-being via virtual learning spaces.

Grounded in these theoretical perspectives, the present study applies the Integrative Student Growth Model (ISGM) to examine how online holistic self-care education influences student stress and resilience. Guided by this framework, the following research questions were developed to investigate changes in perceived stress, relationships between stress and resilience, and students' perceptions of their holistic self-care learning experience:

1. Are there significant differences in online undergraduate students' self-reported levels of perceived stress and resilience when comparing before and after completion of an online ten-week for-credit holistic self-care course?
2. Are undergraduate students' self-reported levels of perceived stress and resilience significantly related?
3. What are the perceptions of online undergraduate students who complete an online ten-week for-credit holistic self-care course?

Methods

Ethical Considerations

To adhere to ethical research conduct, before starting the study, the university's Institutional Review Board (IRB) approved the research. Although all students completed the same pre- and post-surveys as part of the course requirements, the researchers informed the students that participation in the study was voluntary and would not affect their final grades. Only one researcher, who was not the course instructor, had access to all the data. Before sharing the data with the other researchers, this researcher de-identified the data and removed any students who did not consent to participate.

Data Collection Procedures

This study used a concurrent mixed methods design, with quantitative and qualitative data collected through pre- and post-course administrations of a Qualtrics survey. At both the beginning and end of the course, all students completed the same set of scales: the Perceived Stress Scale (PSS) (Cohen et al., 1983; Cohen & Williamson, 1988) and the Connor-Davidson Resilience Scale (CD-RISC-10) (Campbell-Sills & Stein, 2007; Connor & Davidson, 2003). Although participation in the research study was voluntary, all students completed the scales and post-course reflections as part of the required course activities. Students who consented to participate allowed their de-identified data to be included in the research analysis, while those who did not consent still completed the same assessments for their personal learning and course reflection.

Measures of perceived well-being are significant as studies have shown a correlation between higher levels of perceived stress and adverse effects on physical health. A longitudinal study by Tawakol et al. (2017) found that increased activity in the amygdala, associated with perceived stress, robustly predicted cardiovascular events in individuals without known cardiovascular disease or active cancer. Similarly, a landmark study by Epel et al. (2004) demonstrated that perceived stress, rather than objective stress, significantly affects telomere length, a marker of cellular aging. In their study, mothers of chronically ill children with high perceived stress had shorter telomeres compared to those with lower perceived stress, despite both groups experiencing significant objective stress. These findings suggest that it is the perception of stress, rather than the stressor itself, that has a profound impact on health, highlighting the importance of measuring perceived well-being.

In addition to the standardized scales, the pre-course survey included demographic questions for students who consented to participate in the research study. The post-course administration of the survey also included additional open-ended questions to examine students' perceptions of the course. Students were encouraged to reflect on their experience in the course and what changes, if any, they experienced. Responses to these open-ended questions provided the qualitative data for the study. The open ended questions included:

In what ways has your experience of school-related stress changed since the start of the course?

Describe any self-care techniques (such as mindfulness, healthy eating, stress management, yoga, breathing exercises, and cultivation of a positive mindset) you felt were especially helpful in addressing your stress, resilience, and/or well-being.

What are your thoughts about continuing with personal self-care practices? What might that look like?

Perceived Stress Scale

The 10-question Perceived Stress Scale (PSS) was used to assess levels of perceived stress before and after the Holistic Self-Care course. Developed by Cohen et al. (1983), this scale measures the degree to which individuals perceive situations in their lives as stressful. It includes questions such as “In the last month, how often have you felt nervous and stressed?” Participants respond using a Likert scale, scoring each item from 0 (never) to 4 (very often). The PSS demonstrates excellent internal reliability and construct validity (Cohen et al., 1983). This scale is widely used in academic research to evaluate changes in perceived stress levels before and after self-care interventions (e.g., Carroll et al., 2024; Murphy, 2021). In this sample, the PSS demonstrated strong internal consistency (Cronbach’s $\alpha = .84$).

Connor-Davidson Resilience Scale

The 10-question Connor-Davidson Resilience Scale was used to measure resilience, one’s ability to cope with stress, with permission from the authors of the questionnaire. The original questionnaire had 25 items, each rated on a 5-point scale from 0 (not true at all) to 4 (true nearly all the time) (Connor & Davidson, 2003). The questionnaire was modified by Campbell-Sills and Stein (2007) to create a 10-question scale, which was used in this study. The scales have demonstrated good internal consistency and test-retest reliability (Campbell-Sills & Stein, 2007; Connor & Davidson, 2003). The CD-RISC-10 demonstrated excellent internal consistency in this sample (Cronbach’s $\alpha = .87$).

Study Sample

All students enrolled in the Holistic Self-Care course during the Winter 2023, Spring 2023, Summer 2023, and Fall 2023 quarters were invited to participate in the study. Out of the total 246 undergraduate students enrolled in the course throughout this timeframe, 109 consented to participate in the study, yielding a participation rate of 44%. Sixty percent of participants provided complete qualitative responses, while the remaining 40% partially completed these items. Table 1 presents the demographic information for the study sample. Of the 109 participants, 77% were female, and 61% were in their senior year. Eighty-three percent had little or moderate experience utilizing holistic self-care strategies; and over half (61%) never meditated.

Table 1*Demographic Information*

Gender	Number	Percentage
Male	22	20.18%
Female	84	77.06%
Non-Binary	1	0.92%
Prefer Not to Say	2	1.83%

Age	Number	Percentage
20-29	105	96.33%
30-39	2	1.83%
40-49	2	1.83%

Current Classification	Number	Percentage
Freshman	0	0.00%
Sophomore	18	16.51%
Junior	25	22.94%
Senior	66	60.55%

Level of Experience with Holistic Self-Care Strategies	Number	Percentage
No Experience	13	11.93%
A Little Experience	51	46.79%
Moderate Experience	40	36.70%
Very Experienced	5	4.59%

Meditation Frequency	Number	Percentage
Daily	1	0.92%
1-3 Times a Week	0	0.00%

4-6 Times a Week	14	12.84%
Intermittently	32	29.36%
Never	62	56.88%

Data Analysis

To gain a comprehensive understanding of the Holistic Self-Care course's impact on students, both quantitative and qualitative data were analyzed. All survey data was exported from Qualtrics to Excel, and pre- and post-survey responses were matched using university email addresses. After the data was matched, responses from students who did not consent to participate were removed, and all email addresses were deleted to de-identify the data. For the quantitative data analysis, SPSS statistical software was utilized for both descriptive and inferential statistics. Dependent paired t-tests and Pearson correlations were used to analyze the quantitative data.

For the qualitative data, a two-cycle coding approach was applied following Saldaña's (2021) coding framework. The first cycle used a combination of descriptive, emotion, and in-vivo coding techniques. Emotion coding was used to capture the emotions the participants were feeling and used codes like *stress*, *anxiety*, *confident*, and *calm*. Descriptive coding summarized the core topics of the participants' responses, with representative codes including *mindset shift*, *emotional recovery*, and *decreased anxiety*. Lastly, in vivo coding preserved participants' authentic voices by using exact words and phrases from their responses.

Subsequently, the codes were thoroughly examined to identify patterns, leading to the identification of themes. The initial coding was conducted by a researcher experienced in qualitative analysis, and to enhance credibility and dependability, the preliminary codes and emerging themes were reviewed collaboratively by the broader research team. After analyzing the quantitative and qualitative data separately, the results were merged. The quantitative data from pre- and post-surveys provided an overarching perspective, while the qualitative data obtained from open-ended survey questions offered insights into the quantitative findings. Triangulation of the data further supported the validity of the findings.

Results

Quantitative

To analyze the quantitative data, dependent paired t-tests and Pearson correlations were used. Ultimately, the results showed a statistically significant decrease in levels of perceived stress and a statistically significant increase in levels of resilience after the students completed the Holistic Self-Care course. Additionally, a statistically significant negative correlation between levels of perceived stress and resilience was found in both the pre- and post-surveys, indicating that students who experienced less perceived stress were more resilient.

Dependent Paired t-tests

Dependent paired t-tests were used to examine the impact of the course on self-reported levels of perceived stress (PSS) and resilience (CD-RISC-10). See Table 2 for dependent paired t-test values.

Table 2*Dependent Paired t-test Values*

	Mean	N	Std Dev	<i>dependent paired t-test</i>			
				t value	Df	Sig (two-tailed)	Cohen's <i>d</i>
Pre-PSS	21.62	109	6.12	7.975	108	<.001	0.76
Post-PSS	16.63	109	5.33				
Pre-CD-RISC 10	25.36	109	6.08	4.586	108	<.001	0.47
Post-CD-RISC 10	27.92	109	5.54				

For the Perceived Stress Scale (PSS), there are 10 Likert-style questions ranging from Never (0) to Very Often (4). The PSS score is obtained by reversing the scores for questions 4, 5, 7, and 8, then summing across all 10 items. Higher scores indicate higher levels of perceived stress. Levels of perceived stress after students completed the holistic self-care course ($M = 16.63$, $SD = 5.33$) were significantly lower compared with levels of perceived stress before students completed the holistic self-care course ($M = 21.62$, $SD = 6.12$); $t(108) = 7.975$, $p < .001$. This finding suggests that the practices within the Holistic Self-Care course helped students manage their stress more effectively, resulting in an overall reported reduction in perceived stress.

For the Connor-Davidson Resilience Scale (CD-RISC-10) there are 10 Likert-style questions ranging from 0 (*not true at all*) to 4 (*true nearly all of the time*). The score is obtained by summing across all items. Higher scores indicate higher levels of resilience. Levels of resilience after students completed the holistic self-care course ($M = 27.92$, $SD = 5.54$) were significantly higher compared with levels of resilience before students completed the holistic self-care course ($M = 25.36$, $SD = 6.08$); $t(108) = 4.586$, $p < .001$. This finding indicates that participation in the course was associated with an enhanced ability to recover from challenges, adapt more effectively to stressors, and build overall resilience.

Pearson Correlation To examine the relationship between perceived stress and resilience, Pearson correlations were used. The data revealed a statistically significant, negative relationship between levels of pre-survey perceived stress and resilience; $r(108) = -.692$, $p < .001$, two-tailed. Similar to the pre-survey, the post-survey data also revealed a statistically significant negative relationship between levels of pre-survey perceived stress and resilience; $r(108) = -.573$, $p < .001$, two-tailed. This negative relationship indicates that students with higher levels of perceived stress tended to report lower levels of resilience.

Qualitative

After analyzing the qualitative data, four themes emerged (1) Stress Management Techniques, (2) Mindset Shift, (3) Decreased Stress Levels, and (4) Increased Resilience. While several students acknowledged ongoing challenges and fluctuations in stress, the overall

consensus indicated that the holistic self-care course played a pivotal role in empowering students to navigate stress more effectively.

Stress Management Techniques

In the open-ended responses, the undergraduate students commented that as a result of the course, they identified ways to cope with their stress. Strategies mentioned included using essential oils, positive thinking, mindfulness, breathing techniques, and meditation. Additionally, students commented on the importance of taking breaks when stressed so they could engage in self-care techniques. Several of the comments that supported this theme include:

“I have found ways to cope with the stress and not let it get to me as much, such as using essential oils as room sprays.”

“I have found that taking a break with meditation is a good way to cope with school-related stress and help refocus myself to get the work done that I need in a less stressful way.”

“I step away from my work for a minute and focus on breathing.”

Decreased Stress

While some students commented that they still experienced quite a bit of stress, and other students mentioned that “school-related stress comes in waves,” overall students felt that the techniques they learned in the course helped them to lower their level of stress. Several of the comments that support this theme include:

“My stress level has gone down since starting the course.”

“I have been able to cope with stress better and manage it better.”

“I feel less stressed and more equipped to handle stress.”

Mindset Shift

Many students who commented that they felt less stressed at the end of the course attributed this positive effect to a shift in their mindset. Students shared how they were able to reframe their academic experience from striving for perfectionism to viewing learning as a journey with inevitable obstacles that they can overcome. Additionally, they learned to accept things they cannot control instead of ruminating on how they wish things were. Several comments that support this theme of a “mindset shift” include:

“I’ve learned to accept that all I can do is the best that I can do, and not become hung up on the little things.”

“I used to be very focused on whether I would get a good grade on an exam, presentation, or paper but now I know that as long as I tried my best, there is no reason to be sad about a bad grade. It can be disappointing but overall I know that on the next assignment, I will do better.”

“I try not to stress about the little things in school anymore. I have learned that I will be okay and get through every obstacle that comes my way in classes and clinicals, and that stressing about it just puts me through the experience twice.”

Increased Resilience

A final theme that emerged from the qualitative comments was “Increased Resilience”. Students acknowledged the inevitability of stress in their academic journey; however, they expressed the ability to now manage their reactions to stressful events through techniques acquired in the course. Students reported a quicker recovery from stressful experiences. This increased resilience translated into improved problem-solving skills and academic performance. The following comments highlight this theme:

“I think I have learned to overcome my stress and be more of a problem solver. I felt like, I got more intelligent, but in a way for problem solving.”

“Since the beginning of this course, my approach to school-related stress has undergone a positive transformation through the incorporation of holistic techniques. They have allowed me to effectively manage stress, leading to a noticeable reduction in overall stress levels and stay focused, particularly during demanding exam periods or high-stress weeks. Overall, this class has improved my academic experience and performance.”

“I am able to get myself centered quickly.”

Summary

In summary, the quantitative data revealed a negative correlation between levels of perceived stress and resilience, indicating that students with lower perceived stress demonstrated higher resilience. Dependent paired t-tests also showed a significant decrease in self-reported stress and a significant increase in resilience after completing the Holistic Self-Care course. These quantitative findings were reinforced by the qualitative data, in which students described learning and applying a range of self-care strategies they learned in the course, including meditation, mindfulness, breathing techniques, aromatherapy with essential oils, positive thinking, and taking restorative breaks. Although several students acknowledged ongoing challenges and fluctuations in stress, they reported that the course helped them manage stress more effectively. Many also noted that they were able to reframe their academic experience to focus more on the learning journey rather than solely on grades, which contributed to a more balanced academic perspective and improved problem-solving. Taken together, the integrated quantitative and qualitative data highlight the course’s multifaceted benefits in equipping students with practical self-care skills that enhanced resilience and support more effective navigation of perceived stress.

Discussion

Stress is pervasive across programs of study and continues to affect undergraduate students well beyond the academic setting (Karyotaki et al., 2020). With rising rates of mental health issues and increasing social and academic pressures (Dong et al., 2024), universities are called upon to support students in navigating higher education successfully (Brewster & Cox, 2022; Mintz, 2022). To that end, this study examined the impact of an online ten-week Holistic Self-Care course on students' perceived stress and resilience.

Study results affirm the value of the Integrative Student Growth Model (ISGM), which emphasizes holism and self-care as essential to student success (Patestos et al., 2019). Grounded in these principles, the course introduced practices designed to nurture the well-being of the whole person—mind, body, and spirit—through a combination of didactic and experiential learning. The modules included stress-management and self-care practices, such as breathing techniques, self-hand massage, brain breaks, and strategies for improved sleep and test anxiety; mindfulness and meditation practices; nutrition and its impact on overall health; movement and spirituality practices (e.g., yoga, tai chi); and strategies for a growth mindset, improved self-efficacy, and positive self-talk. The varied applications and practices aligned with the ISGM through the concepts of caring, holism, and diverse learning needs.

This intentional design of the course fostered a supportive online learning environment that encouraged consistent engagement in self-care practices, resulting in a reduction in perceived stress and an increase in resilience. Quantitative results revealed significant reductions in perceived stress and increases in resilience, while qualitative findings highlighted improved coping, greater self-awareness, and more positive outlooks. The quantitative data also demonstrated a clear inverse relationship between stress and resilience, consistent with previous research showing that as resilience strengthens, perceived stress tends to decrease (Rees, 2015; Li et al., 2024). This reinforces the complementary nature of these constructs within the ISGM framework, in which enhanced coping and adaptive capacity serve as buffers against stress. Students described using new strategies to manage challenges, indicating that the learning extended beyond the course into their daily lives. Together, these patterns illustrate the ISGM's central idea that caring for the whole person fosters both academic and personal growth.

Another key insight from the qualitative data was that students connected with different techniques based on their personal preferences and needs. Offering multiple strategies supported autonomy, inclusivity, and engagement, hallmarks of the ISGM's holistic and individualized approach. Providing opportunities for choice allowed students to build personalized self-care toolkits that reflected their own values and circumstances which students described as helping them cope more effectively, feel less stressed, and recover more quickly when stress arose. As such, no single practice can fully explain the observed reductions in stress or increases in resilience. Rather, the improvements may result from a synergistic effect, in which the combination of diverse self-care practices, breathing techniques, mindfulness, movement, nutrition, and reflective exercises worked collectively to reinforce well-being. This synergy likely emerged through students' individualized engagement with the practices most meaningful to them, aligning with the ISGM's emphasis on autonomy, holism, and the integration of mind, body, and spirit.

Beyond individual outcomes, the findings align with current research on post-pandemic student well-being. College students continue to report increased stress, loneliness, and academic pressures (Barbayannis et al., 2022; Zhang et al., 2025). The ability of students in this study to develop greater resilience and manage stress more effectively suggests that structured, skills-based courses can help address these ongoing challenges. As students learn to use holistic self-care practices, they strengthen their capacity to adapt, which may positively influence their mental health, academic persistence, and overall life satisfaction.

Collectively, the results contribute to the growing evidence that structured self-care education can enhance stress management, coping skills, and resilience among undergraduate students (Boardman et al., 2016; Heath et al., 2020). Integrating similar holistic self-care courses into undergraduate curricula may strengthen student well-being, improve academic outcomes, and equip learners with skills that extend far beyond the classroom.

Limitations and Future Directions

This study demonstrates the feasibility and promise of delivering holistic self-care education online to reduce stress and support resilience; however, several limitations should be acknowledged. Because this was not an experimental design, causation cannot be attributed to the course itself. Without random assignment or a control group, alternative explanations for the observed effects are possible. Participation was also voluntary, with only 44% of enrolled students completing both pre- and post-assessments. While this raises the possibility of selection bias, no data were collected on nonparticipants, so the extent of its influence is unknown. The reliance on self-reported measures may introduce response bias and limit the ability to verify behavioral changes objectively. In addition, the participant group was predominantly female and composed largely of upper-level students, which restricts the generalizability of the findings and underscores the need for replication with more diverse and first-year student populations. Variability in the course delivery across instructors may have also influenced the consistency of the learning experience. Furthermore, post-assessments were collected near or during Finals Week—a time typically associated with heightened stress—which may have affected the results. Finally, the absence of long-term follow-up prevents assessment of whether benefits were sustained over time.

Future studies should aim to include greater demographic and academic diversity, incorporate objective outcome measures, maintain consistency in instructional delivery, and examine the long-term durability of outcomes. Research comparing results across different academic terms and institutions could also provide valuable insight into how timing, setting, and context influence the effectiveness of holistic self-care education in higher education.

Conclusion and Recommendations

The online course evaluated in this study used an asynchronous format to connect students, instructors, and content in meaningful ways, reducing barriers of time and distance. Across ten weeks of holistic self-care practice, students reported lower perceived stress and greater resilience. These variables were inversely correlated, indicating that students who demonstrated higher resilience tended to report lower perceived stress. This relationship underscores the interdependence of stress regulation and resilience-building and suggests that strengthening one capacity may reinforce the other. Students' qualitative reflections illustrated

how these shifts translated into daily life, describing greater self-awareness, more adaptive coping, and practical strategies for managing academic and personal challenges.

These findings indicate that structured holistic self-care education can support student well-being and persistence. As stress and burnout continue to affect college populations, integrating evidence-informed self-care within the curriculum offers a practical pathway for cultivating self-awareness, emotional balance, and healthy coping. Purposeful inclusion of these opportunities can strengthen students' capacity to navigate demands during college and beyond.

The results should be interpreted in light of the study's limitations. Future research should standardize core instructional elements, recruit more diverse samples across class years and demographics, and add objective and longitudinal measures to assess the durability of effects. Replication across institutions and academic disciplines may clarify contextual influences and inform best practices in holistic self-care education.

Overall, this study affirms that universities share responsibility for whole-person development alongside academic achievement. Providing structured, accessible opportunities to learn and practice holistic self-care can prepare students to meet complex demands with skill and confidence. Embedding holistic self-care within higher education can help institutions create learning environments that empower students to flourish personally, academically, and professionally.

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Caring School Leadership and Enabling School Structure: A Predictive Study on the Psychological Capital of Online Educators

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Abstract

Teacher attrition continues to be a concern in the American school system. There are several reasons for teacher turnover, such as teachers perceived lack of administrative support and control over their work. Research has found several leadership styles to have a positive correlation to psychological capital, also known as PsyCap. The purpose of this study was to examine the extent to which caring school leadership and enabling school structure may predict online teachers' psychological capital. The study asked state-certified teachers in an online charter school in the northeastern United States to complete a self-report survey using the instruments of the Psychological Capital Questionnaire (PCQ-12), Caring School Leadership Questionnaire (CSLQ), and Enabling School Structure (ESS) survey. There were 152 participants who completed the survey. A multiple linear regression was conducted, and the results found a statistical significance in the extent caring school leadership and enabling school structure may explain the psychological capital of online teachers, demonstrating a large effect size. Even though virtual schools are a different type of school context, this study supports previous research on how positive leadership models and styles are antecedents to psychological capital. Since caring school leadership is a relatively newer construct, this study also adds to the literature by demonstrating it has a positive predictive correlation to online teachers' psychological capital.

Keywords: Psychological capital, caring school leadership, enabling school structure, online school, virtual school, cyber school

Jensen, R. S. (2026). Caring school leadership and enabling school structure: A predictive study on the psychological capital of online educators, *Online Learning*, (30)2, 603-621. <https://doi.org/10.24059/olj.v30i2.4792>

Before the pandemic of 2020, there was already concern about teachers' well-being and the high percentage of teachers leaving the profession (Burkhauser, 2017; Castro et al., 2018). Some studies indicate that upwards of eight percent of teachers leave the profession every year (Carver-Thomas & Darling-Hammond, 2017; Kurland, 2019). There are mixed reports on the extent of the increase in teacher turnover that occurred during and after the pandemic, but some researchers see the current teacher attrition rate as similar to before the pandemic (Goldhaber & Theobald, 2023). The issue of teacher attrition is significant because when teacher turnover is high, studies have found that it can have a negative impact on school culture (Burkhauser, 2017; Carver-Thomas & Darling-Hammond, 2017) and student outcomes (Fuller et al., 2018; Geiger & Pivovarova, 2018). To address this negative trend of higher levels of teacher attrition, it is important that school leaders consider the triggers that may lead to this phenomenon. Research has found that low level of job satisfaction, lack of organizational commitment, teacher perception of low control in their work, and lack of administrative support were significant factors in teacher turnover (Chambers Mack et al., 2019; Geiger & Pivovarova, 2018; Jeon & Wells, 2018; Kurland, 2019).

School leadership has been found to be a significant component in addressing teacher retention as well as in establishing a culture where teachers sense they can thrive and improve work outcomes (Burkhauser, 2017; Carver-Thomas & Darling-Hammond, 2017; Geiger & Pivovarova, 2018; Perrone et al., 2019). The concept of teachers being able to thrive is addressed within the field of positive psychology, which focuses on how an individual's positive experiences and strengths can lead them to flourishing and experiencing contentment, success, and improved performance (Bozgeyikli, 2017; Gyu Park et al., 2017; Jensen, 2020).

From within the field of positive psychology, the theory of psychological capital emerged (Gyu Park et al., 2017; Luthans et al., 2016; Pitichat et al., 2018). This theoretical construct explains how psychological resources can help individuals improve work outcomes and their quality of life (Luthans et al., 2015; Luthans & Youssef-Morgan, 2017). This is relevant in examining patterns of teacher job satisfaction because of the positive correlation found between psychological capital and job satisfaction (Luthans et al., 2015; Manzano-Garcia & Ayala, 2017). Based on this understanding, the research question for this study was:

RQ: To what extent do caring school leadership and enabling school structure predict psychological capital for certified teachers in an online school?

In other words, as a multiple linear regression study (Keith, 2019), the focus was to examine the extent to which caring school leadership and enabling school structure can explain the phenomenon of the psychological capital of teachers in an online school where the school leadership uses virtual means to guide, influence, and direct teachers who primarily work remotely. This is a replication study; the original was conducted before the pandemic (Jensen, 2020). Now that society appears to have normalized into a post-pandemic world, the researcher wanted to find out if the results had changed from the original study.

Even though online schools have exponentially grown over the past decade or so (Leidner & Roch, 2024; Martin et al., 2020; Skousen & Vogel, 2024), there is limited research conducted within this educational model (Sivia & Robertson, 2022). Even within the realm of online education, models can vary from more asynchronous to synchronous (Alzahrani et al., 2023). An asynchronous model is structured for students to work through the online curriculum independently, where the teacher serves more as a facilitator. In contrast, the synchronous model is structured to use an online platform to provide a real-time,

interactive classroom environment where students have immediate interaction with their teachers and classmates (Alzahrani et al., 2023).

Most of the research conducted on virtual schools focused on student engagement and the academic performance of students (Martin et al., 2020; Sivia & Robertson, 2022; Waddell, 2017). Even though there is a growing number of studies specifically examining school leadership in a virtual context and the influence on employees within online schools, there is still a need for more research (Gustafson & Haque, 2020; Sivia & Robertson, 2022; Skousen & Vogel, 2024). Research on the working conditions of teachers in virtual schools has found that teachers reported strong administrative support (Leidner & Roch, 2024; Wiyono et al., 2023). There are significant differences between being a school leader in a brick-and-mortar school compared to the same experience in a virtual school (Partin & Derrington, 2023), whereas others have found no significant difference, but recognize the unique responsibilities and functions that a virtual school leader will encounter (Gustafson & Haque, 2020; Skousen & Vogel, 2024). For example, one competency that all leaders must demonstrate is communication, but for the leaders of online schools, there is the uniqueness of developing effective e-communication skills utilizing information and communication technology (ICT) (Gustafson & Haque, 2020; Skousen & Vogel, 2024).

Even when examining the wider field of e-leadership of virtual teams in general, there is still minimal research (Ahuja et al., 2023; Chua & Chua, 2017; Van Wart et al., 2019). However, several studies in e-leadership corroborate the findings specific to virtual school leadership that emphasize communication using ICTs (Ahuja et al., 2023; Van Wart et al., 2019). It has also been found that leaders of virtual teams may positively impact the well-being and motivation of the members of their teams. Due to the remote nature of employees working virtually, the online school leader needs to be even more focused to minimize feelings of isolation or loneliness (Ahuja et al., 2023; Van Wart et al., 2019). For this reason, it is beneficial to see what aspects of school leadership in online schools can positively impact teachers in thriving and flourishing within an environment that leads to them functioning at their fullest potential.

Literature Review

Psychological Capital

Luthans and Youssef-Morgan developed the theory of psychological capital. Luthans and colleagues (2015) define psychological capital as:

An individual's positive psychological state of development that is characterized by (1) having confidence (efficacy) to take on and put in the necessary effort to succeed at challenging tasks; (2) making a positive attribution (optimism) about succeeding now and in the future; (3) persevering toward goals and, when necessary, redirecting paths to goals (hope) in order to succeed; and (4) when beset by problems and adversity, sustaining and bouncing back and even beyond (resiliency) to attain success (p. 2).

There are several criteria that were established as being necessary in the construct of psychological capital, including the need to be state-like, a higher-order construct, and psychological resources that are strength- and evidence-based (Carter & Youssef-Morgan, 2022; Luthans et al., 2015; Petersen & Youssef-Morgan, 2018). To be state-like, it was intended that the theory be malleable and able to change over the course of time (Alessandri et al., 2018; Luthans & Broad, 2022; Pitichat et al., 2018). To know that an individual's

psychological capital is able to change highlights the importance of the work environment (Alessandri et al., 2018). As a higher-order construct, it means the whole is greater than the individual parts. In other words, the overall measure of psychological capital is of more significance than the four psychological resources it incorporates, and the four resources work synergistically (Alessandri et al., 2018; Luthans et al., 2015; Viseu et al., 2016).

Based on the four psychological resources of hope, efficacy, resilience, and optimism, Luthans and Yousseff-Morgan (2017) have referred to psychological capital as “the HERO within” (p. 339; see also Luthans & Broad, 2022). The concept of hope, which was first developed by Snyder, includes both goal pathway and goal energy, with pathway being the way one maps out the strategy to achieve their goal, and energy being the motivation and agency to persevere until the goal is accomplished (Carter & Youssef-Morgan, 2022; Jensen, 2020; Luthans et al., 2015). Efficacy is associated with Bandura’s theory and focuses on one’s level of confidence based on positive feedback, observing models of success, reflection on one’s own performance, and one’s response to various situations. Masten researched how a person responds to setbacks and established the theory of resiliency that looks at the mechanisms individuals use to persevere and overcome challenges. The final psychological resource that makes up psychological capital is optimism. This is associated with attributional style theory that emerged from the research of Seligman, Carver, and Scheier and focuses on how a person develops the expectation of achieving a positive outcome (Carter & Youssef-Morgan, 2022; Luthans et al., 2015).

The construct of psychological capital has been well-researched since it was first introduced (Luthans et al., 2015), including several meta-analyses (Kong et al., 2018; Loghman et al., 2023; Wu & Nguyen, 2019). The most comprehensive meta-analysis examined 244 studies published during the period of 2007 to 2020 (Loghman et al., 2023). The findings of these meta-analyses were consistent with findings related to the outcomes of psychological capital, such as improved work performance, higher job satisfaction, and increased employee engagement (Kong et al., 2018; Loghman et al., 2023; Wu & Nguyen, 2019).

The research has found that positive leadership styles are a significant antecedent to psychological capital (Loghman et al., 2023; Luthans et al., 2015; Luthans & Youssef-Morgan, 2017). In particular, several studies have examined various leadership styles, such as leader-member exchange, transformational, and authentic leadership models, and have found that there is a positive relationship between these leadership styles and the psychological capital of employees (Hu et al., 2018; Kong et al., 2018; Loghman et al., 2023).

Psychological capital has also been found to be associated with positive outcomes of employees (Alessandri et al., 2018; Loghman et al., 2023). Some of the positive outcomes that are important, when looking to improve teacher retention, include work performance (Huang et al., 2015; Kong et al., 2018) as well as the reduction of stress, anxiety, and employees’ intentions to leave (Luthans et al., 2016; Manzano-Garcia & Ayala, 2017; Xue et al., 2023). One particular study, which has significance for teachers at an online school, focused on technostress, which is the stress associated with learning new technology programs. This study found a negative correlation between technostress and psychological capital (Efilti & Coklar, 2019). Research also revealed that psychological capital has a positive relationship with the level of employee engagement in their work, which included informal workplace learning (Alessandri et al., 2018; Huang & Wang, 2021). When psychological capital is high, studies have found positive relationships with the overall well-being of employees (Kun & Gadanecz, 2022; Kurt & Demirbolat, 2019; Manzano-Garcia &

Ayala, 2017), job satisfaction (Kong et al., 2018; Kurt & Demirbolat, 2019), and one's commitment to the organization (Karakus et al., 2019). Based on the wide-ranging positive outcomes of psychological capital, and the positive correlation with leadership styles, it is beneficial to see if caring school leadership and enabling school structure can also assist in explaining the phenomenon of teachers' psychological capital.

Caring School Leadership

The research on the positive impact of demonstrating caring in the helping professions is extensive, but the concept of caring school leadership is still in its infancy (Berkovich, 2023; Kurland; 2019; Louis et al., 2016). Most of the educational research on caring is related to the teacher-student relationship and its positive impact on students (Eldor & Shoshani, 2016; Kurland, 2019; Nilsson et al., 2015). In recent years, more research has examined the theory of caring school leadership and its influence on both students and faculty (Louis & Murphy, 2017; Smylie et al., 2016; van der Vyver et al., 2014a).

Even though the concept of care is recognized, there is not an agreed upon definition of caring school leadership, as the construct continues to evolve (Louis et al., 2016; Ryu et al., 2022). Based on the perspectives of different researchers, caring school leadership is multifaceted, incorporating the cognitive, affective, and behavioral domains (Jensen, 2020; Louis et al., 2016; Steilen & Stone-Johnson, 2023). Caring school leadership includes reciprocity, interdependence, and recursivity (Houghton et al., 2015; Louis et al., 2016; Nilsson et al., 2015). A working definition of caring school leadership is the positive relational connection of a school leader with the employees of the school, whereby the leader demonstrates service to others and genuine regard for their interests, needs, and overall well-being (Jensen, 2020; Steilen & Stone-Johnson, 2023). It is also important to note that school context may impact the form of caring school leadership (Ryu et al., 2022).

Caring school leadership is manifested in various forms, including kindness, empathy, fairness, empowerment, and service (Louis & Murphy, 2017; Smylie et al., 2016; van der Vyver et al., 2014a; Younger, 2021). Ultimately, caring school leadership is relational in nature, where the focus is on seeing others develop holistically in both their personal and professional lives (Louis et al., 2016; Smylie et al., 2016; van der Vyver et al., 2014a; Younger, 2021). When van der Vyver (2014b) and his colleagues developed the Caring School Leadership Questionnaire (CSLQ), they grouped different phenomena associated with caring leadership into three main determinants. The psychological determinant includes such actions as sympathy, expressing concern, showing respect for others, honesty, acceptance, and compassion. The management determinant is evidenced by trust, empowerment, active listening, accessibility, and support. The final determinant is associated with the physical space in which teachers work (van der Vyver 2014b). However, since virtual teachers work remotely, this determinant was not included in the study.

Even though there is not a significant amount of research associated with caring school leadership, the studies conducted demonstrate positive outcomes (Ryu et al., 2022; Steilen & Stone-Johnson, 2023). For example, caring school leadership has been found to be related to improving school climate (Kurland, 2019; Louis & Murphy, 2017; Louis et al., 2016). Specifically, caring school leadership can moderate the impact of emotional distance teachers experience, and thereby positively influence school climate (Berkovich, 2023). Not only does caring school leadership impact the climate of a school setting, but it has also been found to be related to improving the emotional well-being of teachers and increasing their performance (Eldor & Shoshani, 2016; Nilsson et al., 2015). Similar to what was found with

psychological capital, caring school leadership is also found to have a positive relationship with reducing stress and improving job satisfaction (Eldor & Shoshani, 2016).

Enabling School Structure

The study of organizational theory focuses on how to make organizations more efficient and effective in achieving their goals (Haveman & Wetts, 2019). Much research has specifically looked at the theory of bureaucracy and the corresponding structure that it manifests within organizations (Mitchell, 2019). The general impression that most people have of bureaucracy is negative in nature, with its rational-legal structure, with more rigid lines of authority and rules (Haveman & Wetts, 2019).

However, some have found that it is not necessarily bureaucracy per se, that is the issue, but rather if the leader uses the authority structures and written rules in a way that is either hindering or enabling (Kilinc et al., 2016; Sinden et al., 2004a). It is from this perspective that the concept of enabling school structure was developed (Hoy & Sweetland, 2001; Sinden et al., 2004b). It is accurate to see schools as bureaucratic organizations, consisting of an authority structure and written rules.

Hoy and Sweetland (2001) postulated that school structure includes the components of formalization and centralization. Formalization alludes to the rules within an organization. Centralization refers to the type of hierarchical authority structure of the organization (Hoy & Sweetland, 2001; Kilinc et al., 2016; Sinden et al., 2004a). It is the *structure* of these components that either enables or hinders teachers to be most effective in their roles.

Formalization and centralization can be conceptualized as existing along a spectrum, the poles of which stretch from hindering to enabling, which impact teachers' ability to perform. A matrix that identifies four types of school structures helps to illustrate how bureaucracy may be perceived (Hoy & Sweetland, 2001). At one end of the matrix is *hindering* bureaucracy consisting of high centralization and coercive formalization, where the overall school culture is characterized by compliance and a dominant leadership style. The *hierarchical* bureaucracy has high centralization, but enabling formalization with few rules, making the school structure more totalitarian, where what the leader says goes. The *rule-bound* bureaucracy is low centralization and hindering formalization, which results in an uncompromising reliance on rules and procedures. Finally, the more ideal structure is *enabling* bureaucracy, with low centralization and enabling formalization (Hoy & Sweetland, 2001).

Some studies have found that enabling school structure has a positive relationship to student academic performance (Anderson et al., 2018; Mitchell, 2019). Just as research found an association of caring school leadership and school climate, similar results were found when looking at the association between enabling school structure and school climate, especially within professional learning communities (Cerit, 2017; Gray et al., 2016). Similarly, enabling school structure can also impact teacher effectiveness (Anderson et al., 2018; Gray et al., 2016; Kilinc et al., 2016). For example, enabling school structure was found to positively correlate to the organizational commitment of teachers (Sinden et al., 2004b).

Materials and Methods

Participants

The participants for this study were drawn from a virtual charter school in the northeastern United States. The study used a purposive, convenience sample, where the participants from the online school were state-certified teachers, and all participants from a single online school system that provides synchronous instruction, by means of online technology platforms. The school setting is structured where there are three grade-band principals, which align with how teachers identified with either being part of the elementary, middle, or high school programs. For a multiple linear regression study, the minimum sample size, with a statistical power of .80 and a .05 alpha level, is $N > 104 + k$, whereby k is the number of predictor variables. For this study, the minimum sample size was 107 (Warner, 2013).

The researcher invited 394 online educators to participate and 183 started the survey. Only those who completed all questions in the survey were included in the statistical analysis, which ended up being 152 participants, which exceeds the minimum sample size. Most of the participants were women ($n = 134$, 88.2%). The majority of the participants were also over the age of 40 ($n = 109$, 71.7%) and had nine or more years of teaching experience ($n = 132$, 86.8%). The distribution among teachers in elementary school ($n = 43$, 28.3%), middle school ($n = 44$, 28.9%), and high school ($n = 65$, 42.8%) is similar to the online school in which the study was conducted.

Psychological Capital Questionnaire (PCQ-12)

The Psychological Capital Questionnaire measures one's overall psychological capital (PsyCap). The original version contained 24 items, but for increased adaptability in research, the developers created a shorter version (PCQ-12) containing only 12 items (Luthans et al., 2014). The instrument measures the four domains of hope, efficacy, resilience, and optimism which are associated with PsyCap. The PCQ-12 contains four items related to hope, three items associated with efficacy and resilience respectively, and two items for optimism (Luthans et al., 2014).

The PCQ-12 uses a 6-point Likert-type scale where 1 = strongly disagree and 6 = strongly agree. The scoring on the PCQ-12 can range between 12 to 72, where higher scores indicate a higher level of psychological capital (Luthans et al., 2014). For purposes of research, a cumulative mean score for each participant was used, where scores closer to six indicate higher levels of psychological capital. The PCQ-12 has been found to be valid and reliable with a strong internal consistency ($\alpha = .88$) (Luthans et al., 2014).

Caring School Leadership Questionnaire (CSLQ)

The Caring School Leadership Questionnaire measures the degree to which teachers feel cared for by their educational leader (van der Vyver et al., 2014a). The instrument contains three determinants: (a) psychological, (b) workplace (physical environment), and (c) management. Since this study focuses on educators who work remotely, the determinant that addresses the physical environment of the workplace was not included. The overall CSLQ contains 59 items, but only 45 items were used including the 25 items for the psychological determinant and the 20 items for the management determinant.

The CSLQ uses a 4-point Likert-type scale where 1 = not at all and 4 = to a large extent. The high score for the psychological and management determinants is 140, with an average caring score being between 88-92 (van der Vyver et al., 2014b). For purposes of

research, a cumulative mean score for each participant was used, where scores closer to 4 indicate higher levels of caring school leadership. The validation study conducted on the CSLQ demonstrated its very strong internal consistency ($\alpha = .98$).

Enabling School Structure Survey (ESS)

The Enabling School Structure (ESS) instrument was designed to measure the degree to which the bureaucratic structure of a school enables or hinders teacher autonomy and their ability to work (Hoy & Sweetland, 2001). The two main factors include formalization and centralization. Formalization focuses more on rules and centralization on the loci of authority in decision-making (Hoy & Sweetland, 2001).

The ESS contains 12 items using a 5-point Likert-type scale where 1 = never and 5 = always. Six of the items are negatively loaded and require reverse scoring. The scores can range from 12 to 60 with higher scores indicating a more enabling school structure (Sinden et al., 2004a). For research purposes, a cumulative mean score for each participant was used, where scores closer to 5 indicate higher levels of enabling school structure. In the validation study, three samples were used and the internal consistency ranged from $\alpha = .90$ to $\alpha = .95$.

Procedure

This study was a replication study that the researcher first conducted in Fall 2019 (Jensen, 2020). In both the original study and in this replication study, an online survey was created using SurveyMonkey. The informed consent was on the first page of the study and then was followed by four demographic questions related to gender, age, school grades taught (elementary, middle, or high school), and years of experience as an educator. To ensure anonymity, IP address tracking was disabled, and the anonymous response option was enabled.

After receiving permission from the chief school administrator of the online school to conduct research among the faculty, the researcher worked with the Human Resources personnel to obtain school-issued email addresses for all teachers within the school system. The researcher sent an introductory email to the faculty of the school introducing them to the purpose and intent of the research study. Participants were then notified of the study, through an automated email generated by SurveyMonkey, which provided the link to the study survey. Participants were given three weeks to complete the survey, with automatically generated reminders to any participants who had either not yet started the survey or had an incomplete survey.

At the completion of the survey window, the researcher used SPSS for statistical analysis. The researcher conducted descriptive statistics that determined the mean, standard deviation, and Cronbach's alpha scores associated with the three instruments used in the study. Then, the assumption tests associated with a multiple linear regression study were completed. Finally, the researcher ran the analysis, which included a regression model, model summary, and analysis of the coefficients.

Results

The research question examined to what extent psychological capital can be predicted from the linear combination of caring school leadership and enabling school structure for certified teachers in a virtual school. There was one case that was greater than 3 standard deviations ($SD = -3.585$), but when leverage values were examined (.054) and an analysis of

the influential point of Cook's Distance (.296) was performed, it was decided to keep the case within the data.

All assumptions for parametric inferential analysis using a multiple linear regression were met. Independence of observations was met by conducting the Durbin-Watson statistics, with a value of 1.71. Visual inspection of scatterplots demonstrated that the assumptions of linearity and homoscedasticity were tenable. The assumption that there was no multicollinearity was also met when examining the statistics of Tolerance (.677) and Variance Inflation Factor (1.477). There was one case ($SD = -3.585$) which was found to be a significant outlier. However, it was kept in the data set after Cook's Distance showed a value of .296, which is considered to be a safe value below 1.0. Finally, a P-P plot was conducted to determine if the residuals were normally distributed, and this assumption was also found to be tenable.

The descriptive statistics included demographic information of the participants, the mean score and standard deviation of the responses of the three instruments, and internal consistency statistics for the three instruments. On a six-point Likert scale, the mean teachers' psychological capital was 4.93 ($SD = 0.59$). On a four-point Likert scale, teachers' perception of caring school leadership was 3.34 ($SD = 0.77$). The teachers' perception of enabling school structure, using a five-point Likert scale, had a mean of 3.53 ($SD = 0.78$). The Cronbach's alpha for all three instruments demonstrated strong internal consistency (PsyCap = 0.858; CSLQ = 0.985; and ESS = 0.927). This is consistent with other studies that have used these instruments (Luthans et al., 2014; van der Vyver et al., 2014b; Hoy & Sweetland, 2001).

The results of the study found evidence that there is a statistically significant association between the predictor variables of caring school leadership and enabling school structure on the criterion variable of online teachers' psychological capital, where $F(2, 149) = 21.38, p < .001$ (Table 1).

Table 1

Regression Model Results

Model		<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>	Sig.
1	Regression	11.63	2	5.816	21.38	<.001 ^b
	Residual	40.53	149	.272		
	Total	52.16	151			

a. Dependent Variable: Psychological Capital scores

b. Predictors: (Constant), Caring School Leadership score, Enabling School Structure score

The overall model size was $R = .472$ and $R^2 = .223$, indicating a large effect size where a little over 22% of the variance of psychological capital may be explained, or accounted for, by the linear combination of caring school leadership and enabling school structure. (Table 2).

Table 2*Coefficients*

Model	Unstandardized Coefficients		Standardized Coefficients	<i>t</i>	Sig.
	<i>B</i>	<i>SE</i>	β		
1 (Constant)	3.436	.239		14.394	<.001
Caring Leadership	.203	.082	.218	2.486	.014
Enabling School Structure	.235	.066	.313	3.565	<.001

a. Dependent Variable: Psychological Capital

Discussion

The results of this study support the findings of the original study (Jensen, 2020), where there was a statistically significant predictive relationship between caring school leadership and enabling school structure on virtual teachers' psychological capital, $F(2, 106) = 19.76, p < .001, R^2 = .272$. In both studies, there was a large effect size found between the linear combination of caring school leadership and enabling school structure in predicting teachers' psychological capital, where the original study found 27% of the variance can be accounted for by this model, and the current study found 22% of the variance of virtual teachers' psychological capital may be explained by the linear combination of caring school leadership and enabling school structure.

As society works to return to normal forms of operation after the pandemic, the results of this study seem to demonstrate that both before and after the pandemic, organizational structure and leadership style may help to explain the variance of psychological capital of online teachers. This finding is significant since schools continue to wrestle with the challenges of teacher attrition and shortages. Job satisfaction and teachers' commitment to the organization have been found to be associated with the level of control teachers feel they have in their work (Chambers Mack et al., 2019; Jeon & Wells, 2018). The current study supports this idea by demonstrating the correlation between online teachers' psychological capital and enabling school structure, which examines the degree the school is more enabling or hindering in the elements of centralization and formalization. Likewise, job satisfaction and teachers' commitment have also been found to be correlated to the degree teachers sense they have administrative support (Geiger & Pivovarova, 2018). This study also supports this by finding that the level of virtual teachers' collective psychological capital, which includes hope, efficacy, resiliency, and optimism, may be explained by the degree they perceive their school leader demonstrating caring school leadership behavior.

The literature identifies leadership style as an antecedent of psychological capital, whereby the research has demonstrated there is a positive predictive relationship with positive leadership styles, such as transformational leadership, authentic leadership, and leader-member exchange (Kong et al., 2018; Loghman et al., 2023; Petersen & Youssef-Morgan, 2018). Even though this study did not specifically examine whether caring school leadership or enabling school structure are antecedents, the study appears to support this prior

research on the impact of positive leadership styles. As a standard multiple linear regression, the current study demonstrated that there is a statistical and practical significance, whereby the relationship of caring school leadership and enabling school structure may explain some of the variance in virtual teachers' psychological capital. Since psychological capital has been found to have positive outcomes such as job satisfaction, work performance, and school climate (Eldor & Shoshini, 2016; Kurland, 2019; Louis et al., 2016), caring school leadership and enabling school structure are models that should be more closely examined when looking to improve the organizational climate and culture of online schools.

This study also contributes to research on virtual schools. Research has found that leadership can have a positive impact on the well-being of employees, though the e-leader may have to utilize different forms of communication tools to be effective (Ahuja et al., 2023). Studies have found that caring school leadership is contextual and the form it takes in one context may not necessarily work in another (Smylie et al., 2016; Ryu et al., 2022). Prior research on caring school leadership has primarily looked at differing brick-and-mortar school contexts. This study expands the look at the unique nature of place, the context in which leadership occurs, by examining it within online schools.

This study found that caring school leadership is also a significant factor within online schools. For example, Berkovich (2023) examined caring school leadership in the context of "emotional geographies," which identified five areas where emotional distance can develop among staff. One of the emotional geographies classified within the theoretical framework of emotional geography is physical distance. Physical distance is defined as educators having limited time to interact and build relationships with colleagues. Berkovich's study found that caring school leadership is positively correlated to minimizing emotional distance. Due to the nature of virtual schools, physical distance is a stark reality for online educators who work remotely. The current study supports Berkovich's findings that caring school leadership may positively predict the combined hope, efficacy, resiliency, and optimism of online teachers. This study supports other studies (Louis & Murphy, 2017; Smylie et al., 2016; van der Vyver et al., 2014a) that encourage school leaders to implement intentional, caring leadership behaviors, such as active listening, transparency, recognizing them for outcomes and accomplishments, and attentiveness by showing genuine interest in getting to know them as individuals. However, more research is needed on the benefits and outcomes associated with caring school leadership, and which leadership behaviors may most contribute to teachers feeling valued and appreciated (van der Vyver et al., 2014a).

It should be noted that there are several limitations to this study. While using a convenience sample from one school system, without random assignment, the results cannot make causal claims and cannot be generalized to all online schools. For example, the school used in this study is more of a synchronous model, whereas many virtual schools use a more asynchronous model. Also, virtual schools can also be structured where the faculty are expected to work from a centralized location, instead of working remotely. Another limitation is that the study was cross-sectional, similar to the original study (Jensen, 2020). However, since the results found in this study, which was conducted at a different time of the school year than the original study, this limitation may not be as significant.

It should also be noted that even though the minimum sample size was met, the overall participation rate from the sample population was about 39%. One possible reason for this could have been the timing of when the survey was conducted, which was near the end of the school year. When considering other limitations, another area that needs to be mentioned is the possibility of confounding variables that may skew the results. For example, in this

particular study, the majority of participants were over the age of 40 (71.7%). Likewise, 86.8% of participants had nine or more years of teaching experience in the online model. These may be factors that impact or influence the results. More research, where these variables are controlled, is recommended.

A core purpose of standard multiple linear regression is explanation; that is, to estimate the degree the predictor variables account for the variance on the criterion variable (Keith, 2019; Warner, 2013). A common limitation of the standard multiple regression is that it does not control for other possible explanations. For example, one possible explanation could be reverse causality. This is when it is assumed that A causes B, but in effect, it may be that B causes A (Sibulkin & Butler, 2019). More specifically, as it relates to this specific study, it is possible that instead of caring school leadership and enabling school structure explaining the variance in psychological capital, it may be the reverse, where psychological capital explains variance in teachers' perception of leadership style and school structure.

This study focused on the association between the criterion and predictor variables, therefore, it is important to also note that another limitation is the study cannot show causation. This is a general limitation of standard, or simultaneous regression analysis, where all variables are entered at the same time. For this reason, a recommendation for future research is to use structural equation modeling to examine the various complex associations between multiple variables and consider alternative explanations or models. Likewise, a causal-comparative study may also assist in addressing the possibility of reverse causality, in which multiple school systems would be examined, where caring school leadership scores and enabling school structure scores are found to be low in one, medium in another, and high in the last, to see if there is a difference in the overall psychological capital scores of the faculty among these three schools.

Another recommendation would be to conduct a mixed-methods study where researchers might find what specific caring school leadership behaviors have a greater impact on the psychological capital of online teachers. Since caring leadership is more art than science (Younger, 2021), it may look different from one context to the next (Ryu et al., 2022). For this reason conducting a mixed-methods study, where a qualitative analysis is incorporated, may help determine if there are trends of certain behaviors and actions of school leaders, which may be identified as resonant with faculty working within online schools, in demonstrating care and concern for the overall well-being of teachers.

Declarations

Institutional Review Board Statement: The study was found to be exempt by the Institutional Review Board of Liberty University.

Conflict of Interest: The author declares there are no conflicts of interest.

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Understanding the Interplay Between Self-Regulated Learning, Student Engagement, and Teaching Behaviors in Shaping Online Learning Readiness

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Abstract

Being prepared for online learning is crucial for educators, instructional designers, and stakeholders in delivering effective educational services. However, research is scarce on the indirect effects of learners' engagement (EOL) and instructors' roles and behavior (IRBL) in online learning readiness (OLR). To tackle this gap, a cross-sectional study was carried out to investigate the role of EOL and IRBL as mediators between self-regulated learning (SRL) and OLR among university students aged 18 to 35 (mean age = 23.8, $SD = 3.40$). Structural equation modeling (SEM) conducted through AMOS was used to dissect the intricate linkages. The study's findings unveiled a significant indirect effect of IRBL on the relationship between SRL and OLR ($\beta = 0.267, p < 0.001$). However, the study revealed that student engagement did not exert a significant indirect effect on the relationship between SRL and OLR ($\beta = 0.006, p > .05$), indicating that student engagement does not act as a mediator in this relationship. Nevertheless, the model fit indices confirmed that the model fit well with the data. Overall, the analysis furnishes compelling evidence substantiating the proposed relationships and mediating effects within the model. This study provides a comprehensive framework for enhancing the quality of education in virtual settings and fortifying OLR by emphasizing both instructor-driven and student-driven components.

Keywords: Online learning readiness, student engagement in online learning, self-regulated learning, instructors' role and behavior

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The global pandemic has brought to light the pressing need for organizations, including higher education institutions, to adapt to future challenges quickly and effectively (Krsmanovic et al., 2024). However, many public universities are slow to embrace change, particularly in integrating online learning, which has emerged as a transformative force in academia (Bygstad et al., 2022). This delay not only hampers the educational opportunities available to students, especially those balancing work or family responsibilities, but also impacts broader community outcomes. Investigating this issue is crucial for understanding how to better implement online education, bridging the gap between traditional practices and modern needs, and ultimately ensuring that all learners have access to quality, flexible educational opportunities.

Academic institutions' continued reliance on traditional, deeply ingrained institutional biases, centuries-old lecture-based teaching methods, and outdated classroom settings underscores the urgent need for change. Online learning (OL) has emerged as an excellent strategy to address these deficiencies and usher in a new era compared to traditional education. Several studies (AlAjmi et al., 2021; Bolliger & Wasilik, 2009; Carrillo & Flores, 2020) have considered the implications of online teaching and learning. Convenience, time efficiency, collaborative work, autonomy in learning activities, and the ability to engage with people across geographical boundaries are among the opportunities provided by online education. Teachers increased student engagement and made studying more exciting by using various tools and applications (Dumbford & Miller, 2018). Assessing the extent to which students are prepared for OL is crucial for the design and delivery of e-learning. However, there have been few studies investigating the underlying mechanism of online learning readiness. Being prepared for the OL process is an important variable to consider for future interventions in an OL environment (Paliwa & Singh, 2021). Therefore, it is important to review critical concepts such as online learning readiness (OLR) to integrate new technologies, instructional methods, and techniques. By observing changes in students' readiness levels in an online learning environment, it is important to consider the theoretical underpinnings of how learners interact with their environment.

Theoretical Framework

Social Cognitive Theory focuses on the concept of triadic reciprocal determinism, which emphasizes the intricate interplay among personal factors, such as cognitive strategies, self-regulation, behavioral characteristics, and immediate environmental factors (Bandura, 1989, 2001). Self-regulated learning is one of the key personal factors in this triadic model, and it is defined by metacognition, goal setting, and intrinsic motivation. These self-regulated processes are important as they allow students to actively participate in learning activities by contributing to discussions, taking the initiative to do assignments, or reacting to online content. This participation is at the core of the success of online learning environments (Luszczynska & Schwarzer, 2015).

Learning engagement functions as a vital self-regulation tool that connects students' internal capabilities to their observable educational behaviors. The active learning engagement of students strengthens their persistence and achievement in online education through improved self-efficacy and better feedback use, and enhanced obstacle resilience (de la Fuente et al., 2021). Online learning engagement (EOL) exists as an indispensable component that allows learners to actively use their self-regulation techniques to become ready digital learners with motivation and confidence, and with adaptability in online environments (Herguner et al., 2020).

Placing EOL as a mediator in this model is not only theoretically sound; it is also a critical behavioral practice whereby the individual self-regulatory capacities of students play a very significant role in learners' perceptions and preparedness for negotiating OLR. Though prior studies (e.g., Ergun & Adibatmaz, 2020; Lin & Dai, 2022) examined individual and environmental factors separately, this model incorporates EOL as a mediator, allowing us to scrutinize the impact of SRL on EOL, and provides new insight to examine learner activity in online learning settings. Engagement in online learning, in particular, is an avenue where self-regulation strategies can be made available and influence confidence, motivation, and learning readiness within the online context. Using research questions that draw out intersections of these variables, this model presents a wider portrait of how students experience online learning. The model provides a vital contribution through its ability to explain how self-regulatory skills and engagement, together with learning outcomes, function dynamically in digital environments. This model addresses the missing elements in current literature regarding this research method while offering researchers a practical framework for future investigations. The model identifies different pathways between these variables during educational environments, yet places EOL as a fundamental element for developing authentic online learning preparedness.

Online Learning Readiness (OLR)

OLR consists of technology capabilities and personal attributes. Personal attributes include a learner's disposition, such as confidence in achieving goals, time management, problem-solving skills, self-motivation, academic ability, and self-control (Dray et al., 2011). Technology capabilities involve basic skills such as using online communication tools, accessing devices and the internet, and engaging with technology regularly (Pham & Dau, 2022; Wei & Chou, 2020). Recent research (Alem et al., 2014; Keskin et al., 2019; Wang et al., 2022) emphasizes the importance of students' knowledge, skills, psychological, social, affective characteristics, and physical opportunities for effective OL.

Students' readiness for online learning, such as work skills and self-directedness, can significantly impact their success, including grades and course completion (Hung et al., 2010; Yeh et al., 2019). Social cognitive theory suggests that effective self-regulation—encompassing goal-setting, self-monitoring, and strategy adjustment—contributes to learning readiness. It emphasizes that personal (self-regulated learning), behavioral (engagement), and environmental factors (instructor behavior) together shape students' readiness for online learning. Various studies (Cigdam & Ozturk, 2016; Dray et al., 2010; Kaymak & Hozram, 2013; Tang et al., 2021; Wang et al., 2022; Warner et al., 1998; Watkins et al., 2008; Wladis & Samuels, 2016; Yu, 2018) have demonstrated the critical role of OLR in student success in online programs.

However, research is scarce on the indirect effects of learners' engagement in OLR. Moreover, a wealth of studies (e.g., Tang et al., 2021; Wang, 2022) have been conducted in recent years, and the findings have provided insight into the role of OLR in determining the effectiveness of OL experience. However, the underlying mechanism through which instructors' role and behavior influence learning readiness remains under-investigated. Additionally, studies (Coopasami et al., 2017; Ranganathan et al., 2022; Yilmaz, 2017) have examined the predicting factors of OLR independently. Based on the available literature, this study appears to be one of the few that integrates all the identified predictors into a single model.

In line with this rationale, Panadero et al. (2016) highlight that self-regulation methods are key determinants of students' success in online learning environments. The study shows that

students who apply self-regulatory methods achieve better engagement levels, together with improved achievement results in digital learning scenarios. The research conducted by Anthony et al. (2019) analyzed SRL and OLR interactions in higher education to determine that students who practiced effective self-regulation methods became better prepared for online learning demands. A study conducted by Artino and Loannou (2008) found that specific self-regulatory aspects, including goal setting alongside self-monitoring serve as essential predictors for students to prepare for online education. According to Azevedo et al. (2009) research, learners who demonstrate advanced self-regulation skills achieve better online learning readiness and engagement results. The collective evidence from these studies demonstrates how essential self-regulated learning serves as a core requirement for online learning readiness despite limited integrated models in academic literature. Research conducted by Martin and colleagues (2020) analyzed 619 articles concerning OL and teaching, which demonstrated that learner characteristics represented the primary study focus at 28.92%. The characteristics were divided into self-regulation, student engagement, motivation, and academic readiness.

Student Engagement

Student engagement consists of several dimensions that involve students interacting with peers and instructors (Boulton et al., 2018). It is commonly understood as a multidimensional concept, including behavioral, cognitive, and emotional components. Behavioral engagement involves observable actions like participation, attendance, and involvement in learning. Cognitive engagement covers self-regulation, deep learning strategies, and sustained academic effort. Emotional engagement reflects students' affective responses, such as interest, enjoyment, and a sense of belonging within the educational environment (Alam & Mohanty, 2024). This framework provides a comprehensive understanding of how students engage with educational settings. Emotional engagement describes students' affective responses in educational settings, such as interest, enthusiasm, enjoyment, and a sense of belonging. This dimension measures the degree to which students experience positive emotions toward learning activities, instructors, peers, and the broader school environment (Skinner et al., 2009).

Online course participation includes active involvement alongside concentration and ongoing commitment. According to Khuhro (2024), students' engagement functions as a mediator between their SRL behaviors and their OL readiness. The environment created by instructors through their responsiveness, together with feedback and support, determines factors that boost student engagement. According to the theory, SRL connects to OLR through environmental factors that establish the learning context (Dai et al., 2023). Numerous research papers, including Dixon (2015) and Henrie et al. (2015), together with Trowler & Trowler (2010), emphasize the role of student engagement in sustaining connections while preventing students from dropping out. Research shows that students who engage more in their learning activities obtain better educational outcomes while staying enrolled in their courses (Abou-Khalil et al., 2021). The implementation of effective engagement methods is essential for online learning since it affects both student success and course completion rates (Salas-Pilco et al., 2022). The mediating impact of student engagement on OLR remains unexplored through empirical research, even though its significance for OL is well established.

Self-Regulated Learning (SRL)

Self-regulated learning consists of three core components, which are metacognitive processes and motivational elements together with behavioral aspects (Zimmerman, 2008). Self-regulated learning proves vital for students to achieve success in online education because these

students require independence and self-direction (Broadbent et al., 2015). Key SRL components such as goal setting, self-monitoring, and reflection are critical for academic performance (Carter et al., 2020) and for effective online learning (Broadbent, 2017; Chen & Hwang, 2018). Research shows that self-regulation skills enhance learning experiences, with specific strategies improving students' OLR (Papamitsiou & Economides, 2019; Hooshyar et al., 2019).

Instructional Factors

The current research gap exists because previous investigations focused mainly on instructor teaching methods, yet failed to investigate how students perceive their learning experiences (Grasha, 1994; Jimola, 2024; Polat, 2023; Vikas & Mathur, 2022). This disparity in emphasis raises important concerns about the overall effect of instructional approaches on OLR. For example, Grasha (1994) provided a thorough analysis of various teaching philosophies and made the case that instructor traits have a big impact on student involvement. However, little is known about how students view these teaching strategies and how they directly affect OLR. This lack of focus causes problems, especially when it comes to comprehending how students perceive and respond to different teaching methods.

Furthermore, there are contradictory results about the impact of particular teaching philosophies on students' readiness for online learning, even though instructional factors have been connected to student achievement. Jimola (2024) notes that some traditional teaching methods may actually hinder OLR and that students may benefit from more participatory and team-based approaches. Moreover, Vikas and Mathur (2022) point out that different student demographics and learning preferences yield varying results from pedagogical approaches. Polat's (2023) evidence highlights the need for more research into these opposing views, as some students do well with direct instruction. This inconsistency shows how important it is to consider the student's perspective, which has been largely ignored in earlier studies. We can't fully understand OLR if we ignore how students perceive and engage with instructional factors. By looking at instructor factors from the student's perspective, this study aims to bridge these gaps by exploring their perceptions and how it affects their readiness for online learning. This study will contribute to the bigger conversation on successful online learning environments by combining the findings of earlier studies to give a more nuanced understanding of the relationship between instructor strategies and student readiness. It will address the contradictions in earlier research and the urgent need to consider the students' perspective in OLR studies.

Instructors have been tasked with restructuring their courses on digital platforms, away from the traditional lecturing mode towards a facilitative one (Damsa & Langford, 2021; Hung et al., 2010). Online teaching is dependent on understanding instructor and student preparedness to ensure effective OL (Sophonhiranrak, 2021). Challenges include the need for instructors to learn digital competencies and adapt pedagogical processes to a digital format (Almazova et al., 2022; Coman et al., 2020). Research emphasizes the necessity for course design, interactivity, and guidelines to enhance student engagement and dropout prevention (Ferri et al., 2020). Evidence obtained by Joosten and Cusatis (2019) demonstrates that instructional factors such as content, interaction, and support are positively correlated with students' success and persistence in online courses. Besides, the instructors achieve critical and reflective thinking by inviting the students to engage in meaningful online discussions, which involve providing feedback, posing probing questions, and engaging in interaction—all of which are necessary to create an enriched learning environment (Bizami et al., 2023). Online instructors are faced with challenges when it comes to assessment because there is no face-to-face interaction. Thus, they must construct tests that

maintain academic integrity and efficiently gauge learning by students (Nkalane, 2018).

In the present study, SRL involves students setting goals, tracking progress, and reflecting on learning. SRL predicts success in OL, but its effectiveness is influenced by student involvement and instructor behavior. Instructors who communicate clearly and create a supportive online environment can enhance student engagement and the use of SRL techniques. Additionally, student engagement in OL serves as a behavioral mediator, translating students' SRL into significant engagement with the platform and course material. Students with high engagement levels can feel more prepared for OL by enhancing their capacity to navigate and thrive in an online setting.

Hence, the objective of the study is to examine the mediating role of student engagement (EOL) and instructor role and behavior between SRL (predictor) and OLR (outcome). The specific hypotheses of the study are: (a) There will be a significant indirect effect of instructor role and behavior (IRBL) between self-regulated learning (SRL) and online learning readiness (OLR). (b) There will be a significant indirect effect of student engagement in online learning (EOL) between self-regulated learning (SRL) and online learning readiness (OLR).

Methods

A cross-sectional survey was used with a correlational method to investigate the role of EOL and IRBL as significant mediators between online SRL and OLR. The cross-sectional correlational design can reach vast and diverse populations quickly and can produce the standardized, quantitative data required for intricate statistical analyses such as mediation. The approach is not only cost-effective but also can examine several variables simultaneously.

Sample and Sampling Technique

The study targeted Pakistani university students aged 18-35 years ($M = 23.8$, $SD = 3.40$) from both genders, with a determined number of participants being ($N = 375$) at 95% confidence level and 5% margin of error through Raosoft sample size calculator (Raosoft, 2023). We also used the Monte-Carlo procedure, with 1,000 replications per condition, tested realistic measurement scenarios such as strong, moderate, and weak factor loadings, and model complexity similar to each scale. We used standard fit-index and parameter-power criteria, aiming for a target power of 0.80. In the main scenario, which assumed moderate loadings (λ about 0.50) and the model structure we used for each scale, the simulation showed that our sample size ($N = 375$) achieves roughly 0.80 power for detecting medium-sized factor loadings and standardized regression paths, as well as for assessing model fit accurately. A total of 450 questionnaires were distributed, of which 380 were completed and returned, yielding a response rate of 83.3%. The sample includes students of both genders from different academic years and fields of study. In particular, 190 were men, and 185 were women. 174 of them were in undergraduate programs (such as BS), and 201 were in graduate programs (such as MS or PhD). Most of the students who took part were from the social sciences, such as psychology, gender studies, mass communication, economics, and business administration. About 40% of the people who took part said they had done online learning before. The courses that participants were taking used a mix of online and in-person learning, with most of the instruction happening in real time. But some parts of the course, for instance, assignments and video lectures, were given at different times. Additionally, purposive convenience sampling was used to collect data from undergraduate and postgraduate OL-course students. This method ensured that our research objectives were sufficiently fulfilled by targeting those with experiential knowledge in OL (Andrade, 2021).

Measures

The scales used in the study were carefully chosen based on several key factors. We selected the instruments to ensure that the measures aligned with the study objectives and were highly pertinent to the research questions and goals. The selected instruments are extensively checked for validity and reliability. Secondly, we ensure the instruments have extremely stable factor structures and high internal reliability. These instruments have been validated in earlier studies of a similar type and are reliable in similar situations. We also prudently selected measures on pragmatic considerations like ensuring optimum time efficiency, maximizing cost-effectiveness, and ensuring ease of administration for researchers and participants.

Online Self-Regulated Learning Questionnaire

The purpose of this questionnaire is to assess the students' self-regulated learning (SRL) processes (Barnard et al., 2008; Barnard et al., 2010). The 24-item assessment uses a five-point Likert scale (strongly agree = 5 to strongly disagree = 1). Although various biases are indicated in the literature, the OSLQ maintained acceptable psychometric characteristics with two different groups of learners in both online and blended learning contexts. The data and psychometric properties over time show consistent significant statistical relationships with academic achievement and epistemological beliefs (Barnard et al., 2008), and even over time (Barnard et al., 2011). The OSLQ six subscales are self-evaluation, task strategies, help seeking, time management, goal setting, and environment structuring. The OSLQ has good alpha reliability with a value of .90 and is deemed acceptable for research purposes in the social sciences. Also, the values of Cronbach's alpha, i.e., .85 to .92 on subscales are acceptable and reliable. The CFA of the scale reveals a good fit of the data, as evidenced by the fit indices (CFI = 0.95, IFI 0.98, RMSEA = .05).

Student Engagement in the E-Learning Environment (EOL)

This scale was developed by Lee et al. (2019) and is utilized to evaluate various indicators of engagement that contribute to an enhanced OL experience. The assessment included 24 items across six factors: psychological motivation (6 items), peer collaboration (5 items), cognitive problem-solving (7 items), community support (3 items), and learning management (3 items). The factors demonstrate high reliability, with an overall coefficient of 0.93. Specifically, each factor has satisfactory Cronbach's α values: learning management (.71), community support (.81), interactions with instructors (.75), cognitive problem solving (.82), peer collaboration (.87), and psychological motivation (.89). These values indicate consistent reliability across all factors. In the study, an overall scale was used to assess its role in online learning readiness. Responses were measured using a Likert scale, with ratings from 1 (strongly disagree) to 5 (strongly agree).

Online Instructor Role and Behavior Scale (IRBL)

The Online Instructor Role and Behavior Scale (Hung & Chou, 2015) evaluates instructional elements in online learning, including course design, technology facilitation, social support, assessment design, and discussion facilitation. It uses a five-point Likert scale and has demonstrated adequate reliability.

Online Learning Readiness Scale (OLR)

The scale comprises 18 items measured on a five-point Likert scale (1 to 5), covering aspects such as self-directed learning, learner control, computer self-efficacy, motivation, and self-efficacy in online communication. The reported reliability of the scale is 0.70 (Hung et al., 2010).

The scales, originally in English, were used without translation, as Pakistani university students are proficient in English. An online survey using Google Forms was conducted to assess the perceived readiness of students enrolled in regular academic programs (UG and PG) in social science departments. Incomplete questionnaires were omitted from the analysis because of a significant percentage of missing responses (exceeding 10% of total items), which may have skewed the results. The overall missing rate for all items was 1%, which is low and easy to deal with. Missing values were addressed using the Missing Completely at Random (MCAR) method. We did Little's MCAR test to show that the missing data mechanism was correct. The test was not significant ($\chi^2 = X$, $df = X$, $p > .05$), which means that the data were Missing Completely at Random (MCAR). This finding corroborates the choice to manage missing data via listwise deletion, as this method is suitable under MCAR conditions.

Ethical Considerations and Procedure

The participants were informed of the strict adherence to privacy terms and conditions through a consent form. Participants were provided with an email address so that they could communicate their queries and concerns regarding the research being conducted. The consent form clearly outlined participants' right to withdraw from the study at any stage. The data was kept confidential. Written informed consent was obtained, and all participant queries were addressed appropriately. Approval to conduct the study was obtained from the ethical review committee of the department (Ref. no: 0988/Ethic/01/S3H/009/DBS).

Statistical Analyses

Data cleaning was conducted before analysis to identify and correct errors in the dataset, thereby minimizing their impact on the study results. Descriptive statistics were used to compute frequency, mean, SD, and percentage for the variables of the study. Mean scores are commonly used to characterize the relationships between the constructs before fully estimating the latent variable model. Given the comparatively high number of items per construct, this method—often referred to as parceling or using composite scores—was selected to lower model complexity, enhance model convergence, and produce stable parameter estimates. The high internal consistency of the scales and previous research support this approach, even though it assumes that the items within each construct are unidimensional.

The collected data was tabulated and analyzed. Before conducting the main analysis, assumptions of normality, multicollinearity, linearity, and homoscedasticity were checked through various graphical and statistical techniques. For instance, the Shapiro-Wilk test was conducted to assess normality of data. The accuracy of the input was evaluated by descriptive statistics produced by SPSS version 21. Frequency tables were reviewed to identify errors in categorical and continuous variables. The checks confirmed no data entry mistakes and all values were within acceptable ranges. With zero missing values, all participants and variables were retained for further analysis.

Confirmatory factor analysis was conducted for each scale to assess whether the measurement model adequately represents each construct. Correlation analysis was conducted between the study variables to assess the strength and direction of the relationships. The following thresholds were used to interpret the strength of the correlation: $0.1 \leq 0.3$ showing weak correlation, $0.3 \leq 0.5$ showing moderate relationships, and ≥ 0.5 revealing strong correlations. Multicollinearity was assessed using the Variance Inflation Factor (VIF), which indicated values of less than three for all predictor variables. Hence, multicollinearity did not pose a problem in the variables. Mediation analysis using the AMOS software was conducted to assess model testing and the indirect relationships among variables. SEM, or Structural Equation Modeling, is a

confirmatory approach, unlike traditional exploratory methods (Akinyode, 2016; Younas & Khanum, 2024). Unlike traditional multivariate techniques, SEM estimates error variances, whereas both observed and latent variables are incorporated. SEM comprises a unifying framework to fit linear models, test for an overall model fit, and compare parameter estimates across multiple groups (Kline, 2023). We used Maximum Likelihood (ML) estimates that are designed specifically for continuous data. The ML procedure yields efficient and unbiased parameter estimates, provided that the data are multivariate normal. Direct and indirect effects were determined with confidence intervals and p-values of significance. In addition, the model fit was examined using other fit indices such as the Root Mean Square Error of Approximation (RMSEA), Cumulative Fit Index (CFI), Incremental Fit Index (IFI), Tucker Lewis Index (TLI), Normed Fit Index (NFI), and the Chi-square to degrees of freedom ratio (CMIN/df). It has been suggested that CFI, IFI, and TLI values of greater than .95, and an RMSEA value less than .08 would be suitable to fit a good model (Hooper et al., 2008; Hu & Bentler, 1999).

Results

Confirmatory Factor Analysis (CFA) was conducted for each scale, and the results indicated a good fit to the data across all measures. Specifically, the EOL scale demonstrated an excellent model fit (CFI = 0.95, IFI = 0.98, RMSEA = 0.05). Similarly, the OLR scale showed a good fit to the data (CFI = 0.97, IFI = 0.93, RMSEA = 0.04). The SRL scale also exhibited strong fit indices (CFI = 0.96, IFI = 0.95, RMSEA = 0.04), indicating a well-fitting model. Furthermore, the IRBL scale revealed acceptable model fit (CFI = 0.93, IFI = 0.97, RMSEA = 0.03). Overall, these results confirm that each measurement model adequately represents the underlying constructs.

Table 1

Descriptives of the Study Constructs

Constructs	Mean (SD)	No. of items	ω	Range		Univariate measures	
				Actual	Potential	Skewness	Kurtosis
1. EOL	68.605 (17.101)	28	.94	25-125	1-125	-.219	-.105
2. OLR	60.078 (13.046)	18	.72	18-90	1-90	-.320	-.017
3. SRL	72.842 (16.523)	21	.91	24-120	1-20	.069	.051
4. IRBL	48.355 (12.513)	16	.72	16-80	1-80	.055	-.040

Note. SRL = Self-regulated online learning; OLR = Online learning Readiness; EOL = Engagement in online learning; IRBL = Instructor Role and Behavior in online learning; SD = Standard Deviation; ω = McDonald's omega

Table 1 shows the mean scores on student engagement in OL as well as OLR, indicating moderate variability around the average levels of student engagement and learning readiness. Also, the mean value of the IRBL scale indicates a moderate level of perceived instructor effectiveness, with some variation among students' perceptions. However, the mean of SRL scale reveals that while most students exhibit a fairly high level of self-regulation, there is still some variation around this average. Additionally, the McDonald's omega values for all scales are greater than .70 showing adequate reliability and internal consistency of the scales. The values of skewness and kurtosis are close to zero, showing the symmetric distribution of data.

Table 2*Correlation Between Study Constructs*

Sr.No.	Constructs	1	2	3	4
1	EOL	-	.395***	.667***	.426***
2	OLR		-	.548***	.487***
3	SRL			-	.488***
4	IRBL				-

Note. SRL = Self-regulated online learning; OLR = Online learning readiness; EOL = Engagement in online learning; IRBL = Instructor role and behavior in online learning

Table 2 presents the correlations, indicating the significant positive relationships among four key constructs in OL: EOL, OLR, SRL, and IRBL. The strongest correlation is between EOL and SRL ($r = 0.667$), indicating that higher self-regulation is strongly associated with greater student engagement. Moderate positive correlations are observed between EOL and OLR ($r = 0.395$), EOL and IRBL ($r = 0.426$), OLR and SRL ($r = 0.548$), OLR and IRBL ($r = 0.487$), and SRL and IRBL ($r = 0.488$), suggesting that each of these constructs is interrelated, with effective online resources and instructor behaviors contributing to both self-regulation and overall student engagement. All correlations are statistically significant, underscoring their importance in the OL environment. Given these significant interrelationships, the data provide a strong basis for conducting model testing to investigate potential mediation effects, particularly how factors like student engagement and instructor role and behavior might mediate the impact of SRL on OLR.

Figure 1

Structural Equation Model showing the mediation of instructor role in engagement (EOL) and learning readiness (OLR)

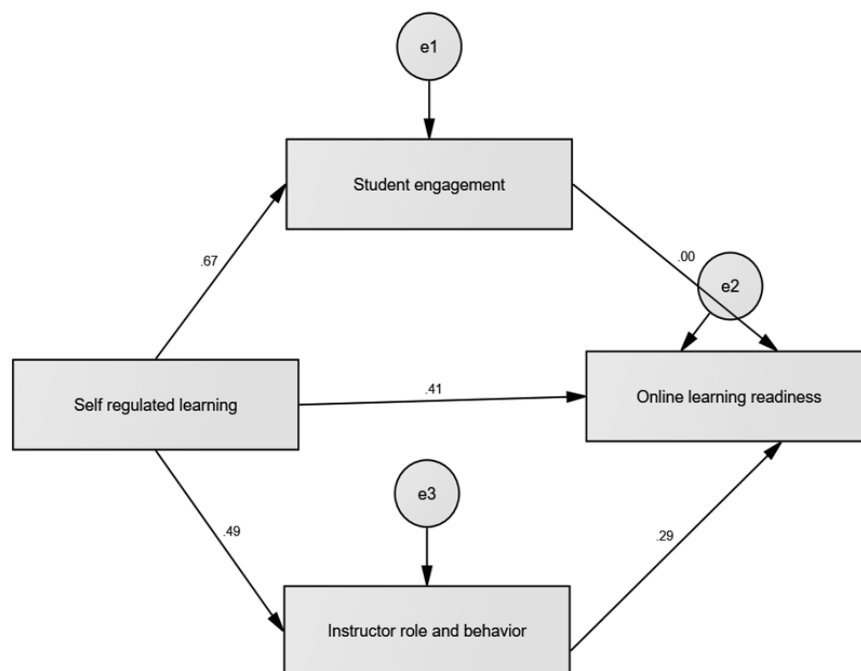


Table 3*Mediation of student engagement, instructor role and behavior in learning readiness (OLR)*

Relationship	β Coefficient	Bootstrap confidence interval		SE	t	Decision
		LL	UL			
Direct effects						
SRL -> OLR	.428	.308	.548	.061	7.023***	
SRL -> EOL	.690	.612	.768	.039	17.395***	
SRL ->IRBL	.369	.302	.436	.034	10.866***	
EOL -> OLR	.006	-.083	.084	.042	.015	
IRBL -> OLR	.300	.202	.398	.049	6.034***	
Indirect effects						
SRL -> IRBL -> OLR	.267	.090	.214	.031	6.034***	Indirect effect supported
SRL -> EOL -> OLR	.006	-.082	.080	.040	.015	
R ² = .238						
Model Fit						
CMIN/DF 9.243; CFI = .984; IFI = .984; TLI = .901; NFI = .982; RMSEA = .05; AIC = 35.243						

Note. SRL = Self-regulated online learning; OLR = Online learning readiness; EOL = Engagement in online learning; IRBL = Instructor role and behavior in online learning; β = Effect size; R² = Variance; SE = Standard error; LL = Lower Limit; UL = Upper Limit

Table 3 provides insights into the relationships between SRL, OLR, EOL, and IRBL. The direct effects reveal that SRL has a strong positive effect on OLR ($\beta = 0.428$, $p < 0.001$), indicating that students with higher self-regulation are better prepared for online learning. SRL also has a very strong positive impact on EOL ($\beta = 0.690$, $p < 0.001$), suggesting that self-regulation is closely related to higher engagement levels. Additionally, SRL significantly influences IRBL ($\beta = 0.369$, $p < 0.001$), meaning that self-regulation positively affects perceptions of instructor behavior and role. The direct effect of EOL on OLR is not statistically significant ($\beta = 0.006$, $p > .05$), indicating that engagement in online learning does not directly influence readiness for online learning. However, the effect of IRBL on OLR is moderate and significant ($\beta = 0.300$, $p < 0.001$), suggesting that more effective instructor roles and behaviors are positively associated with online learning readiness.

Regarding indirect effects, SRL significantly impacts OLR through IRBL ($\beta = 0.267$, $p < 0.001$), highlighting that the effect of self-regulation on online learning readiness is partly mediated by instructor role and behavior. Hence, hypothesis (a) is supported. Conversely, the indirect effect of SRL on OLR through EOL is not significant ($\beta = 0.006$, $p > .05$), suggesting that engagement does not mediate the relationship between self-regulation and online learning readiness. Therefore, hypothesis (b) is not supported. Moreover, the variance (R²) in the outcome variable, i.e., online learning readiness, is 0.238, showing 23% variance in online learning readiness is contributed by the predictor variables.

The model fit indices suggest a good overall fit of the model to the data. The (CMIN/DF) is 9.243, which is on the higher side but acceptable depending on the context. The CFI, IFI, and NFI are all above 0.90, indicating a good model fit. The TLI is slightly lower at 0.901, while the

RMSEA is 0.05, suggesting a good fit as values below 0.08 are considered acceptable. Overall, the analysis provides robust evidence supporting the hypothesized relationships and mediating effects within the model.

Discussion

The study investigates the role of SRL, EOL, and IRBL in OLR among students in higher education. The aim of the study arises from the lack of studies evaluating the indirect effect of IRBL in OLR. Building upon the conceptual framework introduced earlier, which positioned SRL as the primary predictor, engagement and IRB as mediators, and OLR as the outcome, this study empirically tested these relationships using SEM. In the discussion, the results of descriptive, correlational, and SEM analyses are interpreted in light of prior studies and theoretical viewpoints, offering potential justifications for the observed patterns.

Results of descriptive statistics reveal a moderate variability in mean scores for EOL and OLR, suggesting that while these factors are generally stable across the sample, there may be some individual variations. Several variables, including course content, student motivation, and prior online learning experience, may have an impact on this variability. Similarly, the moderate perception of instructor effectiveness, with some variation, highlights the importance of consistent and effective teaching practices. High self-regulation among students, with some variability, suggests that while many students are self-managing well, there is room for improvement in supporting those who struggle. Moreover, the McDonald's omega values above .70 confirm the internal consistency of the scales used, and the skewness and kurtosis values close to zero indicate symmetric data distributions. The correlation analysis shows significant positive relationships among key online learning constructs. The strongest correlation is between engagement in OL and SRL ($r = 0.667$), indicating that higher self-regulation is strongly linked to greater engagement. Moderate correlations are observed between engagement in OL and OLR ($r = 0.395$), EOL and IRBL ($r = 0.426$), OLR and SRL ($r = 0.548$), OLR and IRBL ($r = 0.487$), and SRL and IRBL ($r = 0.488$). These findings suggest that effective OL is influenced by a combination of effective instructor behavior and strong self-regulation skills, which contribute to enhanced student engagement. The findings are also supported by past research (Lasekan et al., 2024; Li & Xue, 2023).

The SEM results demonstrate a robust and positive effect of SRL on OLR (refer to Table 3). This unequivocally indicates that students with higher levels of self-regulation are more adept at effectively utilizing online resources. These findings strongly support existing literature (Torrington et al., 2023; Zhang, 2023), emphasizing the crucial role of self-regulation in navigating and thriving in OL environments. Self-regulated learners excel in managing their learning strategies and adapting to online formats (Zhou & Thompson, 2023). Furthermore, the strikingly significant positive effect of SRL on EOL (refer to Table 3) underscores the pivotal function of self-regulation in promoting heightened levels of engagement. These results undeniably align with previous studies, strongly indicating that self-regulation boosts motivation and engagement levels in learning activities (Al Mamun & Lawrie, 2023; Pintrich, 2004).

Additionally, the significant positive effect of SRL on IRBL (see Table 3) suggests that students who exhibit self-regulation have a more positive perception of the roles and actions of their instructors. Earlier research also gives evidence of the association of self-regulation with

enhanced student-instructor relationships, thereby resulting in more positive interactions with instructors and better use of feedback (Karlen et al., 2023; Schunk, 2005). On the other hand, the non-significant direct effect of engagement on OLR indicates that engagement in online learning does not directly impact readiness for OL. This means that engagement may matter sometimes and sometimes may not directly prepare students for OL.

Engagement, however, may relate to readiness through mediators such as self-regulated learning and instructor support (Chitra et al., 2022). It then becomes necessary to understand how instructors can help promote engagement and how this relates indirectly to readiness. There are also online learning contexts that can influence the relation between engagement and readiness. Engagement could actually affect readiness gradually over a longer period of time. This is where teachers need to focus: creating and sustaining engagement, but also addressing factors that are directly related to OLR. Investigating these may produce better results in online learning. Another reason may be the various contextual factors in Pakistani universities, including cultural attitudes toward education, which may hinder engagement in online settings; technological availability and its reliability affecting the students' access to online resources; and instructional design, which may not be conducive to engagement. Collectively, these features emphasize the complicated linkage between SRL and OLR and demonstrate that more contextual factors should be explored to understand student engagement in online learning environments.

Additionally, the significant and moderate effect of IRBL on OLR (see Table 3) indicates that perceptions of instructor behavior and roles are associated with higher OLR. This is consistent with research highlighting the significance of instructor support in online education (Bernard et al., 2014) and supports the idea that supportive instructor behavior adds greatly to students' preparation for OL. As far as the indirect effects are concerned, the study found a significant indirect effect of SRL on OLR through IRBL (see Table 3), highlighting the effect of self-regulation on OLR partially mediated by perceptions of IRBL. This implies that favourable teacher behaviours may help self-regulated learners, which improves their preparedness for OL.

The model fit indices indicate a strong fit to the data. However, it is important to note that the ratio of 9.243 slightly exceeds the standard cutoff point of 5, suggesting a potential issue with model fit. Nevertheless, it should be considered that the sample size and model complexity may influence this index. If other fit indices are favorable, a higher ratio may still be appropriate in larger samples or more complex models (Shi et al., Maydeu-Olivares, 2019). It is crucial to take into account other indices that support a strong fit in this specific case.

A good fit between the model and the data is unequivocally demonstrated by indices such as the CFI, IFI, and NFI, all of which exceed 0.90. These values indicate that the model effectively represents the data and explains a significant portion of the variance (Lacobucci, 2010). Additionally, the TLI, at 0.901, is still within an acceptable range but falls short of the optimal cutoff of 0.95. The TLI rewards simpler models that obtain a good fit by accounting for model complexity. Value of 0.90 suggests that the model is generally effective while taking into consideration its complexity, though a higher TLI would be preferred (Dash & Paul, 2021). A satisfactory value is indicated by an RMSEA of 0.05, which is substantially within the permissible range (below 0.08). The lower values of RMSEA are generally considered good. This index demonstrates how well the model represents the data without introducing undue inaccuracy.

Limitations

The findings are limited in their generalizability due to the cross-sectional nature of the data. Also, the study did not consider various moderating factors that may affect the current findings. Additionally, it was not possible to make a comparison between students who attend face-to-face classes and those who participate in online learning classes, limiting insights into the comparison of two groups of students. Moreover, we used self-report measures, which may lead to biases such as social desirability and common method variance. This could affect the accuracy of participants' responses. Furthermore, since SRL is grounded in a situational perspective, it is inherently context-dependent and may vary across different learning environments. Subsequent research could enhance its comprehensiveness and contextual relevance by integrating diverse data sources or observational techniques to better capture SRL.

Furthermore, the study employs a dual mediation model. It is important to note the limitations of mediation analysis for cross-sectional data, including failure to establish temporal precedence and potential bias in indirect effect estimates (Cole & Maxwell, 2003; Maxwell & Cole, 2007). Still, the analysis provides a preliminary examination of the proposed indirect relationships, and there is theoretical justification for the model. We encourage researchers to adopt experimental or longitudinal designs in future studies to establish causality for these effects.

Study Implications

The study suggests that teachers can enhance students' OLR by fostering an environment that supports SRL. It demonstrates that SRL not only impacts students' preparedness but also influences their perceptions of instructors' roles, highlighting the reciprocal relationship between student self-regulation and teacher behavior.

Instructors should prioritize effective communication, organized course structures, and positive interactions to improve students' perceptions. Professional development should focus on online teaching strategies like interactive content, prompt feedback, and creating a supportive environment. Educators and course designers can integrate programs that promote SRL behaviors, such as goal setting, progress tracking, and reflection, using technologies that help students monitor their progress and personalize their learning. The findings also help identify students with low self-regulation and engagement who may be at risk of poor online readiness. Tailored interventions, such as coaching in time management and goal setting, can support these students, enhancing their readiness and reducing attrition rates.

Our results substantiate and build upon SCT (Bandura, 2001) by demonstrating the interaction between personal, behavioral, and environmental factors in online learning to provide empirical support. Specifically, we established that self-regulated learning, reflecting the personal domain, had a substantial effect on the embodied learning (the behavior domain) that then led to online learning. Furthermore, the instructional and research-based learning (IRBL) acted as an environmental factor exhibiting significant indirect effect on online learning through embodied learning. This mediation process shows that the intention and action of providing support and readiness from instructors does not simply relate to readiness directly, but through student engagement.

These findings contribute to SCT by providing a context-specific process in which environmental and personal factors together influence outcomes in online learning. Next, we

offer a more nuanced conceptual model for online learning that reflects SCT triadic model, while accounting for digital-specific constructs to better explain how learner readiness emerges from the combined engagement of self-regulation, instructor support, and behavioural engagement in embedded online situations.

Conclusion

The study found a significant effect of the teacher's role and behavior in OLR. The theory implications argue for the necessity of refining existing models of OL by taking into account these factors' specific roles, while the practical implications provide actionable strategies for teachers, curriculum developers, and schools to improve the OL process and outcomes. This study offers a complete framework for enhancing the quality of education in virtual settings and OLR by emphasizing both instructor-driven and student-driven components.

Declarations

There is no conflict of interest among the authors.

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Pre-Service Teachers in the Italian Context: What Influences Their Acceptance of Distance Education?

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Abstract

The willingness of educators to introduce opportunities for Distance Education (DE) remains uncertain despite the substantial use of such approaches during the COVID-19 pandemic. The aim of the study is to identify which factors may influence DE acceptance in a sample of Italian pre-service teachers from different subjects. Following the General Extended Technology Acceptance Model for E-learning (GETAMEL), we hypothesized that perceived ease of use and perceived usefulness may predict intention of future use of DE, which is an indicator of DE acceptance. We also hypothesized that a social factor (such as subjective norm) and a contextual factor (such as facilitating conditions) could influence perceived ease of use and perceived usefulness. One hundred and fifty pre-service teachers ($F = 139$; average age 37.11 years) completed the Teacher's Acceptance of Distance Education Scale (TADES) and its factor structure was verified by a Confirmatory Factor Analysis (CFA). Results emerging from a Path Analysis confirmed our hypotheses in part. Implications to promote future use of DE in higher education are discussed.

Keywords: Distance education, pre-service teachers, technology acceptance; secondary school teachers

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The introduction and adoption of technology mediated opportunities in the delivery of teaching and learning cannot yet be assumed, despite the substantial use of such approaches during the COVID-19 pandemic. Indeed, the sudden and forced use of technologies during this period elicited mixed reactions from teachers and students (e.g., Hoofman & Secord, 2021; Son et al., 2020). In their review of the literature, Faridah and colleagues (2021) showed how each education sector (primary and secondary education, higher and vocational education, and special education) had distinct perspectives on online learning and its challenges (e.g. internet connectivity for pre- and early school, primary and secondary school, and lack of students' motivation for online learning in higher education), and how varied the strategies were to overcome them. Furthermore, Sari and Nayir (2020), in their study with administrators, teachers, and educators across different school levels, found that the most important challenges for teachers were difficulties in internet access, lack of infrastructure and classroom management. Some of the strategies that emerged to tackle these problems included introducing changes in classroom management, seeking help from others who were more digitally skilled (e.g., colleagues, family members and experts), and using different tools (e-mail, phone, WhatsApp) to maintain communication with parents and students. Authors concluded that the participants lacked the support, specific training, and experience needed for distance education (DE).

Perspectives from around the world have highlighted variation in the potential advantages and challenges of DE for students in higher education (Masalimova et al., 2022). Although DE was already present in university contexts prior to the pandemic, its adoption was less common in lower levels of education, particularly in Italy. Therefore, the long-term effects of the pandemic on online teaching and learning across education contexts remain unclear (Cairney & Kippin, 2022). In their review of 27 articles on DE in higher education during COVID-19, Masalimova and colleagues (Masalimova et al., 2022) found that DE had been implemented to varying degrees over the years, offering advantages for students, including flexibility to learn at any time and from any location. However, the extensive use of digital devices in isolation during the pandemic contributed to a variety of physical and psychological concerns, including fear, anxiety, stress, and attention problems.

Access to digital tools alone is insufficient for delivering effective education programs, even during the forced adoption of DE. This has been clearly described by Papadakis (2023) in a review, which reports how even MOOCs—considered one of the best online alternatives to the traditional education system—faced many significant challenges. Papadakis highlights how one of the most relevant, and still underexplored, factors, is the quality of the content made available via MOOCs. This raises broader concerns about the consistency between educational content and the "containers" to which such content is entrusted. Indeed, attention should be paid to avoid the temptation to merely dump content designed for face-to-face formats onto digital platforms (Xie et al. 2018).

Kerres and Buchner (2022) report a rich debate spanning both university and lower school levels. They argue that the use of digital technology in teaching and learning, and the future widespread adoption of technologically mediated learning, will largely depend on the interpretation and re-construction of experiences during the pandemic. Two contradictory visions for the role of educational technology post-pandemic are possible: a pre-digital view that implies a return to "normal," and a post-digital view calling "for a digital normality" that tries to utilize the experiences of the pandemic for a consequential reform of education. Therefore, it is logical to think that the way in which both educators and more general users perceive the introduction of DE in different educational settings today is likely to have been

influenced by their experiences during the COVID-19 pandemic. For example, Mushtaha and colleagues (Mushtaha et al., 2021) examined how engineering students (N = 1,486) and faculty members (N = 227) at the University of Sharjah (Dubai) responded to the abrupt transition. While flexibility was a key advantage of online learning, over half of their participants raised concerns regarding mental health and socialization, with most expressing preference for more flexible models of delivery blending face-to-face and e-learning techniques rather than solely depending on either one of them. While the perceptions of DE reported in this study may have been influenced by the COVID-19 context, the efficacy of blending diverse modes of teaching and learning is echoed in other studies (Amenduni & Ligorio, 2022; Kumar et al., 2021; Megahed & Hassan, 2022).

The acceptance of DE is influenced by factors that predate the pandemic, as documented in existing literature. To better understand these influences, DE acceptance is often framed within the broader concept of “technology acceptance,” defined as the user’s positive decision to adopt technology in their professional practice, which can be expressed in terms of intention to use and the current use of a technological innovation (Ifenthaler & Schweinbenz, 2013; Simon, 2001). Taking a broader view of technology, some authors have observed that even the intention to respond to online surveys is shaped by pre-pandemic factors. Lavidas et al. (2022) clearly shows that teachers’ likelihood of responding to web-based surveys is conditioned by factors such as the authority of the person/institute launching the survey; incentives for answering; survey design; ethical issues; reminders and pre-notifications; and the time when the survey was received. If a routine digital task like answering a survey requires such a complex set of conditions, working professionally online is even more complex.

Several theoretical models explain the conditions under which technological innovation can be used within professional and educational contexts. The Technology Acceptance Model (TAM) (Davis, 1989; Davis et al., 1989), originally used to understand computer acceptance (Davis et al., 1989), is rooted in the Theory of Reasoned Action (TRA; Fishbein & Ajzen, 1975) and the Theory of Planned Behavior (TPB; Ajzen, 1991). According to the TRA, a person's behavior is driven by intention, which is shaped by attitudes towards the behavior (the positive or negative judgment that people attribute to a certain behavior) and subjective norms (the influence that the opinions of others exert on the individual's choices). In the TPB, Ajzen (1991) extended the TRA by adding "Perceived behavioral control" (the confidence that an individual has in her/his own ability to successfully complete a specific task) as a factor that can influence behavioral intentions, TAM builds on these theoretical foundations by postulating that the actual use of a technology is closely connected to the intention to use it, which in turn is determined by the perception of its usefulness and ease of use (Venkatesh & Davis, 1996).

The Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) builds on TAM by integrating core elements from several different models of technology acceptance. UTAUT explains the acceptance of new technologies introduced in professional contexts through four main factors: performance expectancy, effort expectancy, and social influence - which predicts behavioral intention -and facilitating conditions (e.g., technical infrastructure), which predict actual use. Performance expectancy is defined as the degree to which an individual believes that using the system will help them to improve their job performance. Effort expectancy is the degree of ease associated with the use of the new system. Social influence is the degree to which an individual perceives that socially important others believe they should use the new system. Facilitating conditions identify the degree to

which an individual believes that an organizational and technical infrastructure supports the use of the new system.

More recently, Abdullah and Ward (2016) developed an extended version of TAM, the General Extended Technology Acceptance Model for E-Learning (GETAMEL). Based on a quantitative meta-analysis of 107 papers, the authors identified the most common external factors previously cited as predictors of technology acceptance. GETAMEL foresees that the strongest predictor of student's perceived ease of use of e-learning systems is likely self-efficacy, followed by enjoyment, experience, computer anxiety, and subjective norm. In addition, the strongest predictor of students' perceived usefulness of e-learning systems is likely enjoyment, followed by subjective norm, self-efficacy, and experience. Applying GETAMEL, Rizun and Strzelecki (2020) found that enjoyment was the strongest predictor of DE acceptance among undergraduate and graduate students, with self-efficacy also playing a significant role by influencing both perceived usefulness and ease of use. These perceptions, in turn, shape students' attitudes toward DE and their intention to use it in the future.

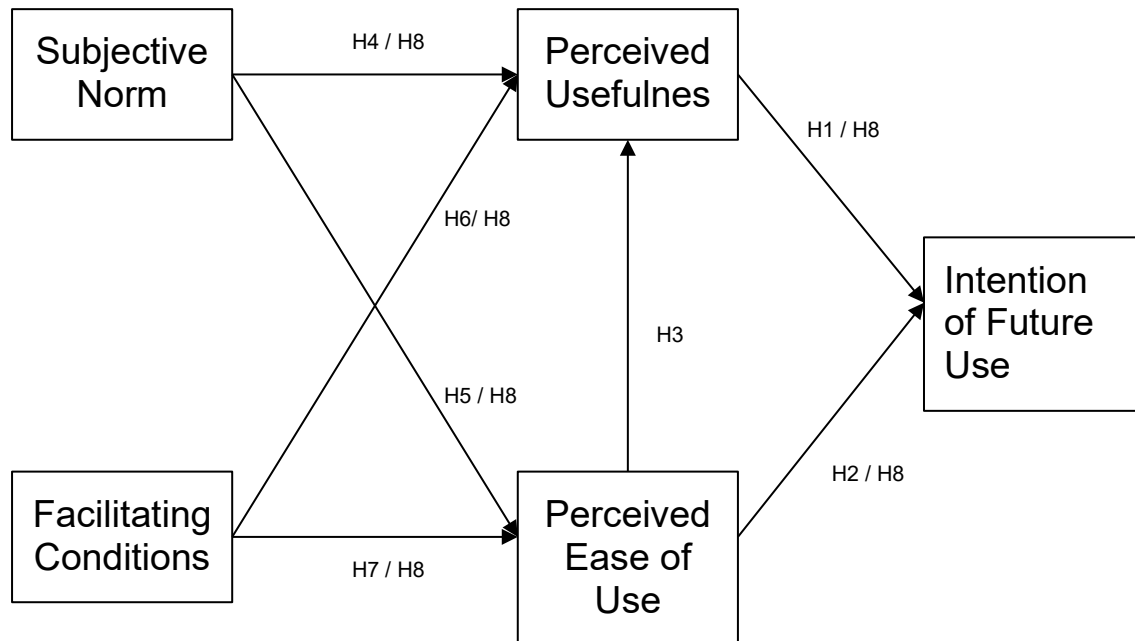
TAM and its extensions have proved to be a sound theoretical model for studying the adoption and acceptance of many technological innovations, including tablets (Author et al., 2018), e-learning (Teo, 2010), telemedicine (Kamal, et al., 2020), gamified learning tools (Luo, 2024), and virtual reality (Manis & Choi, 2019). Furthermore, TAM has also been applied DE, as shown in a recent study investigating Italian DE's university professors' acceptance of DE (Cacciamani et al., 2022). In these studies, the users' positive decision to adopt technology in their professional practices is considered central to DE acceptance.

The use of DE during the Covid-19 pandemic was pervasive. Understanding the factors that influenced teachers' acceptance of DE during this period can provide valuable insights into potential drivers and barriers to acceptance. Such insights are essential for promoting more effective use of DE in the post-pandemic era, where a “new normal” perspective in education is desirable. To this aim, we analyze which factors may have influenced pre-service secondary school Italian teachers' DE acceptance during the second wave of COVID-19 pandemic.

In our opinion, even though DE experience during COVID may have been negative for many teachers, it is important to reflect on the factors that influenced the acceptance (or non-acceptance) of DE during this time, to ensure the lessons learned influence the development of future iterations of DE provision. While the second wave of COVID-19 put teachers to the test from a more psychological point of view (Lizana & Lera, 2022), some studies have reported that teachers perceived a qualitative shift during the second wave, attributed to the support received by principals and colleagues (Barnová et al., 2021). Investigating this period offers insights that are less influenced by the initial shock and novelty of the first wave.

Guided by the GETAMEL framework, we are interested in understanding whether external factors of TAM, such as subjective norms and facilitating conditions, can have positive effects on the perceived ease of use and perceived usefulness of DE. To our knowledge these factors have not been considered until now in analysing preservice teachers' acceptance of DE.

In addition, we intend to verify whether internal factors already included in the TAM—perceived ease of use and perceived usefulness—predict the intention to use DE in the future. Our hypotheses are synthesized in Figure 1.

Figure 1*Research Model*

Hypothesis 1 (H1): Perceived usefulness has a positive effect on intention of future use of DE.

Hypothesis 2 (H2): Perceived ease of use has a positive effect on intention of future use of DE.

Hypothesis 3 (H3): Perceived ease of use has a positive effect on perceived usefulness of DE.

Hypothesis 4 (H4): Subjective norm has a positive effect on perceived usefulness.

Hypothesis 5 (H5): Subjective norm has a positive effect on perceived ease of use.

Hypothesis 6 (H6): Facilitating conditions have a positive effect on perceived usefulness.

Hypothesis 7 (H7): Facilitating conditions have a positive effect on perceived ease of use.

Hypothesis 8 (H8): Perceived usefulness and perceived ease of use will mediate the relationship between subjective norm and facilitating conditions and intention of future use of DE

The results of the study will allow us to extract useful information to better understand the implications of using DE—especially for pre-service teachers—and to design more efficient DE settings for pre-service teachers' training.

Method

Participants

Participants in the study were enrolled in an Active Training Internship (ATI) that consisted of a theoretical and practical training period aimed at professionalizing teaching. At the end of the course, participants take a teaching qualification exam and obtain a professional qualification enabling them to apply for permanent teaching positions in lower secondary schools. The ATI course was delivered by the University of Bari and attended by 150 teachers (Female = 139; Age $M = 37.11$ years, $SD = 7.19$ years) with an average of 3.69 years ($SD = 4.03$ years) teaching experience.

Most participants were employed in the South of Italy ($N = 141$). Seventy-five participants taught in primary schools, 66 in lower secondary level, one in both grades, and seven were not employed in a teaching position at the time of data collection. Data collection was carried out exclusively online from February to March 2021. Teachers were contacted by members of the research team via emails containing information about the study, informed consent, and the survey link. All participants voluntarily signed their informed consent forms, allowing for the use of their data for the research. Ethical principles were observed throughout the study. Ethical committee approval was not deemed necessary as the data collected was concerning teaching approaches on a university course and since data were collected through an online questionnaire and no personal information was required other than age, gender, and school level.

Materials

A translated and adapted version of the Technology Acceptance Measure for Preservice Teachers (TAMPST) questionnaire (Teo, 2010b), one of the most used tools to study technological innovation acceptance, was used to explore factors influencing DE acceptance in school contexts. All items were first adapted, replacing the terms “computer” or “technology” with DE. Four additional items were included to capture a dimension entitled “The intention to use technology in the future,” inspired by Lee et al.’s (2017) questionnaire and assumed as an indicator of DE acceptance. A back-translation technique was used to ensure concordance between the English and the Italian versions. Items were translated from English into Italian, then from Italian back to English by a different translator. Finally, a native English speaker, not involved in any of the two previous steps, compared the two English versions (the original one and the translation) and inconsistencies were resolved. We called this new version of the questionnaire “Teacher’s Acceptance of Distance Education Scale” (TADES). TADES is composed of five subscales, measuring the constructs reported in Table 1. Items were measured on a seven-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree).

Table 1*TADES Subscales, Definition of the Constructs and Examples of Items*

Subscales	Definition of constructs	Example scale items
Perceived Usefulness (PU; 4 items)	Degree to which a user perceives DE useful in teaching	Using Distance Education will improve my work
Perceived Ease of Use (PEU; 3 items)	Degree to which a user perceives DE is easy to use	I find Distance Education easy to use
Subjective Norm (SN; 2 items)	Degree to which a user perceives that others (e.g., a colleague) believe that DE should be used	People whose opinions I value will encourage me to use Distance Education
Facilitating Conditions (FC; 3 items)	Degree to which technical infrastructures support the use of DE	When I need to use Distance Education, a specific person is available to provide assistance
Intention for Future Use of DE (IFU; 4 items)	Degree to which a user has the intention to use DE in future teaching	In the future I will continue to use some tools for Distance Education

Data Analysis

Descriptive and correlational analysis of the data was conducted using IBM SPSS Statistics 29 (IBM SPSS Statistics, IBM Corporation). Based on a preliminary analysis, no univariate outliers were found. The multivariate outliers in the data were checked, using Mahalanobis distance (Tabachnick & Fidell, 1989) and only one participant was excluded because of the anomalous distribution of scores in the items, therefore, potentially capable of influencing the analyses. Mplus (version 8,6, Muthén & Muthén, 1998–2017) was used to conduct subsequent Confirmatory Factor analysis and Path Analysis. The factor structure of the TADES was verified by a Confirmatory Factor Analysis (CFA). We analysed the prerequisites for conducting CFA, to confirm the adequacy of the sample size and the sphericity of the relationships, through the KMO and Bartlett test. The Mardia test (TADE value = 323, greater than the critical value = 228) verified the non-normality of the multivariate distribution. Robust Maximum Likelihood Estimation was used. The estimation of the goodness of fit of the model was based on the following fit indexes: root-mean-square error of approximation (RMSEA), standardized root-mean-square residual (SRMR), and comparative fit index (CFI). Values between .97 and .1 for CFI, <.05 for RMSEA and SRMR suggest an excellent fit; values higher or equal to .95 and lower than .97 for CFI, between .05 and .08 for RMSEA and between .05 and .10 for SRMR suggest an acceptable fit (Schermelleh-Engel et al., 2003). We relied especially upon SRMR and CFI, because the

literature cautions against the use of RMSEA in the case of models with small degrees of freedom and small sample size, as in the present study. In these conditions, RMSEA often incorrectly indicates a poor-fitting model (Kenny et al., 2015). We used Average Variance Extracted (AVE: acceptable .50 excellent >.70) to assess Convergent Validity and the Fornell Larcker criteria to analyse Discriminant Validity. We also analyzed the internal consistency of the questionnaire using Cronbach's Alpha and McDonald's Omega. Finally, to verify the hypothesis of the study, we ran a Path Analysis. The estimation of the goodness of the model followed the criteria indicated above.

Results

Descriptive Analysis

Among the 149 participants entered in the final analysis, 109 (73.2%) did not receive any formal training before the use of DE in their teaching practice. This is not surprising in the Italian context since there is no formal obligation to participate in training about DE; therefore, we can consider this data as quite representative of Italian pre-service teachers. With reference to the delivery of DE used by the pre-service teachers in their teaching activity, 92 (61.7%) employed synchronous modes of delivery, 49 (32.9%) used approaches that combined synchronous and asynchronous delivery, and only two (1.3 %) used asynchronous communication as their core delivery style. Just one participant (0.7%) adopted a hybrid approach, combining in-person delivery to support a student with special educational needs, with simultaneous online delivery to the rest of the class. Five participants (3.35%) did not provide details of their delivery approach. Most participants (N = 112, 75%) reported using a variety of teaching strategies to support DE, combining front-led teaching with activities to promote students' interaction and active learning, such as group work, discussions, project work, and construction of products. Only 28 (18.8%) respondents reported using traditional lesson delivery approaches (i.e., front-led instruction only) with more passive student engagement and nine (6.04%) did not respond to the question.

Confirmatory Factor Analysis and Internal Reliability of TADES

Preliminary analysis checking the prerequisites for CFA confirmed the adequacy of the sample size (KMO= .81) and correlation among the variables (Bartlett's test= 475,85, $p < .001$). A Confirmatory Factor Analysis (CFA) was conducted to assess the factor structure of the TADES. Results of the CFA indicated an acceptable goodness of fit (CFI = .95; RMSEA = .075; SRMR = .056). With reference to Convergent Validity the values of AVE are for all construct >.50 (PU=0.732; PEU=0.592, SN=.760, FC= .698, BI=.783) showing an acceptable Convergent Validity of the scale. Concerning Divergent Validity, the Fornell Larcker table is shown in Table 2.

Table 2

Fornell Larcker Table

Constructs	PU	PEU	SN	FC	BI
PU	.855				
PEU	.648**	.769			

SN	.737**	.528**	.872		
FC	.449**	.428	.489**	.835	
BI	.866**	.700**	.712**	.370**	.885

**p<.01

As is possible to see, all the values of the correlations between the constructs are lower than the Square Root of AVE values (in gray), except for the correlation between PU and BI. It is possible to justify this exception by considering that in TAM literature, PU is the stronger predictor of BI (e.g. Han & Sa, 2012; Syahrudin et al. 2021). So, we can assume Divergent Validity as a property of the scale.

Internal reliability for the full questionnaire (Cronbach's Alpha .92) and five individual dimensions was satisfactory (see Table 3).

Table 3

Internal Consistency of TADES and its Subscales

TADES and subscales	Cronbach's Alpha	Mc Donald's Omega
TADES overall scale	.92	.94
Perceived Usefulness	.92	.92
Perceived Ease of Use	.81	.81
Subjective Norm	.86	(1)
Facilitating Conditions	.86	.87
Intention of Future Use of Distance Education	.85	.86

(1) Omega cannot be estimated because the number of elements is less than 3.

Correlational Analysis

The zero-order correlations between the constructs of the TADES were examined (see Table 4).

Table 4*Zero-Order Correlations for TADES*

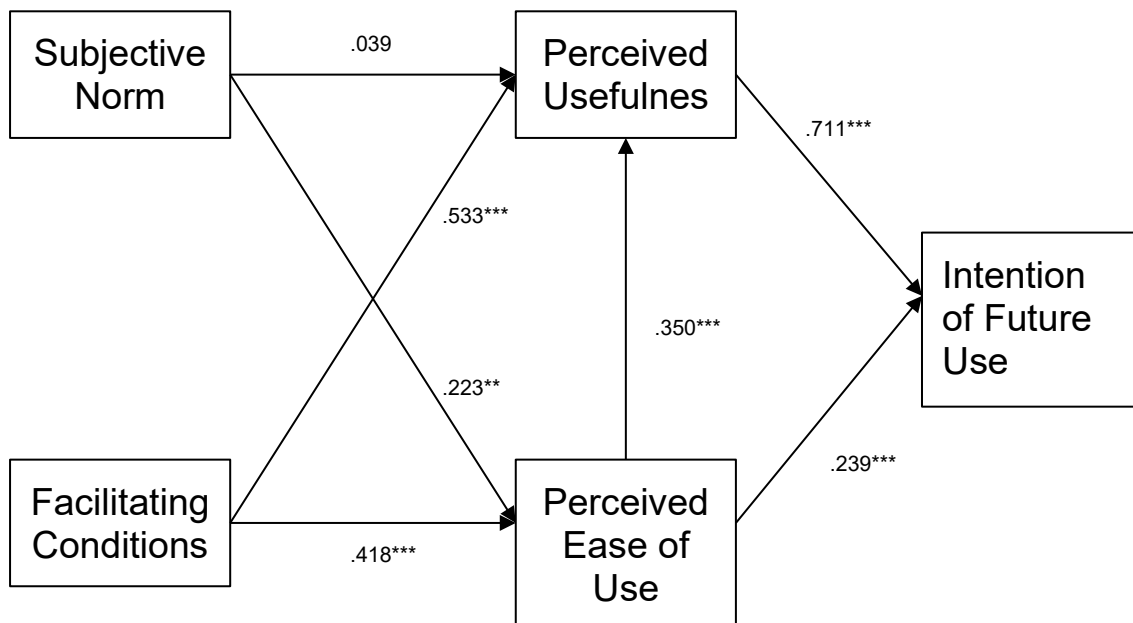
Constructs	1.	2.	3.	4.	5.
1. PU	-				
2. PEU	.648** *	-			
3. SN	.737** *	.528***	-		
4. FC	.449** *	.428***	.489** *	-	
5. IFU	.866** *	.700***	.712** *	.370***	-
M	3.97	4.50	3.34	3.18	4.32
SD	1.40	1.32	1.44	1.45	1.35

*** $p < .001$

Table 4 indicates that, within the considered range (from 1 to 7), the values of intention for future use, subjective norm, and facilitating conditions tend towards the lowest levels of the Likert scale; whilst the values of perceived ease of use and perceived usefulness are close to the average value of the range (4). Significant positive correlations were evident between all variables. Perceived usefulness was positively correlated with perceived ease of use ($r = .648$, $p < .001$), subjective norm ($r = .737$, $p < .001$), facilitating conditions ($r = .449$, $p < .001$), and intention of future use of DE ($r = .866$, $p < .001$). Perceived ease of use was positively correlated with subjective norm ($r = .528$, $p < .001$), facilitating conditions ($r = .428$, $p < .001$), and intention of DE future use ($r = .700$, $p < .001$). Subjective norm was correlated with facilitating conditions ($r = .489$, $p < .001$) and intention of DE future use ($r = .712$, $p < .001$). Finally, facilitating conditions correlated with intention of DE future use ($r = .370$, $p < .001$).

Path Analysis

A structural equation model was used to test the proposed research model and hypotheses. For the observed variables, the model was found to offer an acceptable fit for the data ($\chi^2(2) = 7.53$, $p > .05$; RMSEA = 0.14 CFI = 0.98; SRMR = 0.02). The variance explained by the model ranged from moderate ($R^2 = 0.32$ for perceived ease of use) to high ($R^2 = 0.78$ for intention of future use of DE, $R^2 = 0.64$ for perceived usefulness). The standardized path coefficients are reported in Figure 3 and described below.

Figure 3*Research Model with the Standardized Path Coefficients*

Standardized path coefficients. * = $p < .05$; ** $p < .01$; *** = $p < .001$.

As shown in Figure 3, the standardized coefficients indicated that the paths between perceived usefulness and perceived ease of use to intention of future use of DE attained statistical significance ($\beta = .711, p < .001$ and $\beta = .239, p < .001$, respectively). Moreover, the standardized coefficient relating perceived ease of use to perceived usefulness was statistically significant ($\beta = .350, p < .001$). While the standardized coefficient relating subjective norm to perceived ease of use was statistically significant ($\beta = .223, p < .01$), the path from subjective norm for perceived usefulness was not statistically significant ($\beta = .039, p > .05$). Finally, for facilitating conditions the standardized coefficients of the paths between both perceived usefulness and perceived ease of use were statistically significant ($\beta = .533, p < .001$ and $\beta = .418, p < .001$, respectively). In sum, the analysis of direct paths provided support for the hypotheses tested, except for H4 (the influence of subjective norm on perceived usefulness).

The indirect influence of subjective norm on intention of future use of DE, via perceived ease of use and perceived usefulness (H8) was tested. Significant indirect effects were found via perceived ease of use (standardized estimate = 0.053, $p < .01$; bootstrap 95% CI = 0.021 – 0.086) and via both perceived usefulness and perceived ease of use (standardized estimate = 0.056, $p < .05$; bootstrap 95% CI = 0.020 – 0.091). The indirect effect through perceived usefulness alone (standardized estimate = 0.028, $p > .05$; bootstrap 95% CI = -0.036- 0.091) was not statistically significant. Finally, we tested the indirect influence of facilitating conditions on intention for future use of DE via perceived ease of use and perceived usefulness (H8). Statistically significant indirect effects were evident through perceived usefulness (standardized estimate = 0.38, $p < .01$; bootstrap 95% CI = 0.298 – 0.460), perceived ease of use (standardized estimate = 0.10, $p < .01$; bootstrap 95% CI = 0.058 – 0.142) and through both variables, perceived usefulness and perceived ease of use (standardized estimate = 0.104, $p < .01$; bootstrap 95% CI = 0.061 – 0.148). In sum, the

analysis of the indirect effects showed partial support for H8. All tested indirect effects, except for the path from subjective norm to intention of future DE use via perceived usefulness, were statistically significant.

Discussion

The aim of this study was to verify which factors may influence the acceptance of DE in Italian pre-service secondary school teachers. Drawing on an enriched TAM, the findings confirmed that perceived usefulness (H1) and perceived ease of use (H2) positively affect the intention to use DE in the future. Furthermore, our results showed that perceived ease of use influences perceived usefulness (H3) and that the influence of two external factors, subjective norm (H5) and facilitating conditions (H7), impact perceived ease of use. While facilitating conditions (H6) influence perceived usefulness, subjective norm has no significant impact (H4). Finally, perceived usefulness and perceived ease of use mediate the relationship between facilitating conditions and intention of future use of DE. A significant mediation was also found between subjective norm and intention of future use of DE, via perceived ease of use (H8).

Among all predictors, perceived usefulness emerged as the stronger predictor of the intention to use DE in the future for preservice secondary school teachers. This result confirms previous studies (e.g. Han & Sa, 2012; Syahrudin et al. 2021) highlighting that DE's perceived usefulness positively affects the acceptance of and the intention to use it in the future. This suggests that for pre-service teachers to adopt DE as an innovation in their practice, they need to be reassured that DE can effectively improve their teaching performance. Therefore, pre-service teachers who found DE useful during the second phase of lockdown are more likely to see the value in continuing to use it in their teaching post pandemic.

Interestingly, during the COVID-19 pandemic, DE was primarily delivered through synchronous modes of delivery (for 61% of the preservice teachers). While there was the risk that this would undermine the flexibility normally associated with online learning, it did not reduce the perception of perceived usefulness. This is reflected in the average score for perceived usefulness (3.97 on a 7-point Likert scale). It is plausible that, under conditions of enforced isolation, perceptions of usefulness were based on the opportunity to continue training, rather than on the flexibility of asynchronous online learning.

The present study also confirmed that perceived ease of use influences the intention to use DE in the future. This finding is consistent with other studies across different educational levels (e.g. Al - Al-Alak & Alnawas, 2011; Hong et al., 2021). Conversely, this means that teachers may reject DE if it is perceived as difficult to integrate with their teaching practices. Hong et al. (2021) suggest that pre-service teachers may lack the confidence and ability to use educational technology, instead choosing face-to-face communication and teaching as the preferred approaches in their teaching practices. In such cases, educational technology's simplicity and ease of use would enhance pre-service teachers' willingness to use DE.

Consistent with previous studies, our findings confirm that perceived ease of use influences perceived usefulness (Hong et al.2021; Kelly, 2014). This implies that if DE is difficult to use, it is unlikely to be considered useful, and without perceived usefulness, pre-service teachers are less inclined to adopt and use it (Attis, 2014). Conversely, if DE is easy

to use and perceived as useful, pre-service teachers could be more willing to use it during more critical situations, such as a lockdown, as well as during their normal experience of teaching. This finding has important implications for software developers who should ensure that any proposed educational technologies are easy to use and align with teachers' digital competencies.

An interesting finding of this study concerns the mixed influence of subjective norm on perceived ease of use and perceived usefulness. Other studies, conducted prior to the pandemic period, showed that social influence (a factor very similar to subjective norm in TAM) did not have any effect on perceived ease of use and perceived usefulness (e.g. Elkaseh et al. 2015). For our pre-service teachers, subjective norm appears to have had a positive effect on the perceived ease of use. This may be due to the collaborative support teachers received during the pandemic, as suggested by Sari and Nayir (2021), which helped them navigate DE more effectively. In contrast, perceived usefulness of DE appears to need direct personal experience by the pre-service teachers, and it may therefore not be a result of an action of social influence as foreseen by the subjective norm factor. Consequently, as highlighted by our findings, only perceived ease of use mediates the effect of subjective norm on the intention to use DE in the future.

The significant impact of facilitating conditions on both perceived ease of use and perceived usefulness, and their subsequent mediation of the intention use of DE, highlights the strategic function of this factor during the pandemic. Findings are consistent with previous studies showing the influence of this factor on the intention to use online education (e.g. Waheed & Jam, 2010). Our results suggest that support from the organization should help to promote DE as useful and avoid any complexity in its implementation and use for teaching.

Relatedly, our results emphasize the need for organizations to offer specific training to encourage and support pre-service teachers to move out of their comfort zone and adopt more digital opportunities. Pre-service teachers involved in our study did not have any experience with DE before the first lockdown; therefore, for most of them, the transition towards this new way of teaching was not supported by specific training on digital skills and/or pedagogy. This point has already been highlighted by similar Italian studies, where a lack of digital training was noted in schoolteachers (Giovannella et al., 2020) and university teacher samples (Cacciamani et al., 2022). The different degrees of intention to use DE in the future were subordinate to previous DE experiences, teaching flexibility, and specific training received. To have a better understanding of this point, pre-service teachers with and without previous experiences of the use of DE should be compared. For now, we can only limit ourselves to emphasizing how the absence of specific training makes the acceptance of technological innovations more complex and recommend that teacher training programs include a specific space for the psycho-pedagogical use of technologies.

The role specific training may play in contributing to teachers' DE use has been previously highlighted (Whalen, 2020) but as yet is not sufficiently considered as relevant within teacher training programs. Teachers' need for specialized training is widely reported in the literature. For instance, McCannon and Crews (2000) found that even teachers already using technology need specific training. Teachers often use technology largely for administrative tasks rather than as an integral part of the student learning process. This use of digital technology may provide teachers with an overly optimistic perspective of their own digital skills and in the case of the teachers sampled by McCannon and Crews (2000), may explain why they did not openly express a training need despite the recommendation from the

researchers that staff required support to integrate technology in their teaching strategies. This highlights that teachers' training should be carefully designed, not as sporadic events, with experts offering sustained learning that encapsulates theories, methods, and experiences. In the Italian context, teachers' training is delivered during meetings lasting a few hours, almost always delivered in a traditional lesson mode—whether online or in person—without giving teachers the possibility of monitoring a real transition from what is covered during the lessons to what actually happens in their classroom. Nevertheless, when teachers can participate in a high-quality training program, results confirm the successful impact of the training course on teachers' acceptance of digital tools and practices (Compagnoni, 2022). It is, therefore, clear that high-quality training is needed to truly change teaching practices, supported by powerful reforms (DeMonte, 2013).

The intention to adopt online teaching also plays a relevant role. This dimension, as Tandon (2021) clarifies, is strongly affected by social influence. It is possible that our pre-service teachers made their decisions on whether to accept DE based on the cultural and social conditions connoting their professional contexts. In general, Italian schools are not encouraging the use of DE due to several reasons. In a comparative study conducted by Trevisan and colleagues (Trevisan et al., 2022), Italian teachers reported being less comfortable with DE than their American colleagues, despite the similarities regarding the relevance assigned to the perceptions of institutional support, specific training, and the value both Italian and American teachers assigned to professional development.

Within the cultural dimension, families also play a significant role. Several studies (Author et al., 2022; Cadamuro et al., 2021; Menabò et al., 2022) report that DE in Italy has not been readily accepted by families (Scarpellini et al., 2021) contributing to teacher burnout (Bianchi & Caso, 2022). Furthermore, a recent study (Argentin, 2022) reported that Italian teachers during and after the COVID-19 pandemic recorded a decrease of their job satisfaction, mainly due to a higher workload and a less satisfying relationships with families and colleagues within schools. Nevertheless, teachers demonstrated resilience, as reflected in Argentin's (2022) description of them as "bending but not breaking." While this resilience is encouraging, it does not guarantee that teachers will fully embrace the opportunities offered by DE.

Conclusions

From the perspective of advancing TAM research, this study offers a significant contribution to the influence of facilitating conditions and subjective norms on the acceptance of DE specifically by pre-service teachers. To our knowledge, these factors have not been previously considered in TAM studies with respect to pre-service teachers DE acceptance.

Drawing on our findings and the post-COVID literature concerning Italian teacher's use of DE, and despite the variety in terms of different instructional contexts (e.g. University vs. School) and different degrees of acceptance and use of DE, we can conclude that there is a general convergence between our results and those emerging from the related literature on the following four points:

- (a) The relevance of the following four dimensions in promoting future intention of using DE: perceived usefulness, perceived ease of use, facilitating conditions and, in part, subjective norm;

- (b) The relevance of high-quality training based on psycho-pedagogical models within which to frame the use of technology (Author et al., 2022; Capperucci et al., 2022; Giberti, 2022; Menabò et al., 2022);
- (c) Teachers' capability to face the critical situation is often based on personal resources such as self-efficacy and resilience (Manuti et al., 2022; Guzzo et al., 2002; Porru et al., 2022; Şensin & du Mérac, 2020)
- (d) Teachers are more inclined to adopt blended solutions, where DE is integrated in face-to-face teaching strategies rather than pure DE (Menabò et al., 2022; Guzzo et al., 2023; Pozzi et al., 2023; Taglietti et al., 2021).

Taken together, a rather interesting profile of the Italian pre-service teacher emerges. They are open to innovations—such as DE—provided they perceive them as useful, easy to use, attuned to their personal visions of teaching, and their existing skillsets. This implies that the general model of DE acceptance could be enriched by assigning more relevance to more psychological dimensions, such as self-efficacy. From a practical point of view, this conclusion suggests that the four factors, positively influencing DE adoption in this study, namely perceived usefulness, perceived ease of use, facilitating conditions and in part subjective norm, should be considered as crucial to creating a learning environment favorable for DE's long-term adoption by pre-service teachers.

Teachers and, even more importantly, school leaders and educational institutions, should take into consideration these factors when they want to encourage teaching and learning at a distance. Furthermore, the role of cultural context should also be considered. Future research could explore the role played by the general culture of the institution where the teachers work on how DE and the use of digital resources is perceived. Similarly, it could be interesting to consider the point of view of students and parents and how much they may influence teachers' DE acceptance. These dimensions could also be considered by software developers, to design digital environments aimed at encouraging teachers' DE adoption, involving more actively also students and families.

A few recommendations can be drawn from our results. First, a practical recommendation concerns pre-service teachers' training that should consider how technology is perceived by teachers and the conditions that make it more acceptable. It is no longer possible to consider pre-service teacher training separately from the use of technology. To emphasize this aspect, it is necessary to focus not only on digital skills or digital literacy. It is necessary to consider pre-service teachers' conceptual framework regarding the professional use of technology—which often differs from the framework adopted for personal use (Sansone et al., 2024). Furthermore, it is necessary to highlight the contextual conditions surrounding DE, such as logistical, cultural, and relational support.

This study contributes to understanding the factors that are impacting the adoption of DE by pre-service teachers; nevertheless, a few limitations should be acknowledged. First, the sample is limited and unbalanced from the perspective of gender, since most participants are female. This was unavoidable since Italian teaching staff are composed predominantly of women and our sample reflects this unbalanced national distribution. This is a source of reflection since gender is one of the most investigated factors in relation to technology (Sander, 2005). Most studies concerning attitudes toward technology have found that gender differences are relatively small at younger ages but increase with age (Else-Quest, 2010; Goswami & Dutta, 2015). Since it is almost impossible in our national context to have a

balanced sample in terms of gender, it would be interesting to inquire about changes of attitude for our female teachers along their educational trajectory as well as according to their training and teaching experience. This could seed insights on the socialization processes impacting technology use and its impact on DE acceptance. A longitudinal study should be considered a future research development.

Second, the sample is in a Southern Italian region; this makes the results not generalizable, and we had no intention to do so. Rather, we wanted to obtain an articulated understanding of DE acceptance, whilst also considering cultural and contextual characteristics. The gap between North and South is known in many countries and Italy is no exception, although lately Musolino (2018) has underlined that the “perception gap” is bigger than the “reality gap.” The author claims that the Southern Italy stereotype is much too negative and does not reflect reality. Future research should consider the differences between North and South considering teachers’ DE acceptance to confirm or not the “digital divide” implied by the stereotype. It should also be noted that the pandemic had heavier effects in the North of Italy compared to the South and this may have influenced DE acceptance more than the regional location. As noted, we recognize the limitation in terms of external validity and generalizability, but the characteristics of our sample allow us to reflect upon cultural, social, and gender-specific factors that are not fully representative of broader populations.

Third, we acknowledge that the data collection for this study was undertaken during the COVID-19 restrictions. The extended periods of enforced online teaching and learning provided a unique opportunity for educators to gain experience of and reflect on DE approaches, and therefore the findings of this study present value in framing potential post-pandemic considerations of DE adoption and integration.

For future research, we will expand the sample and explore contextual dimensions, such as institutional attitudes toward DE, school location (North vs. South), educational level (primary vs. higher education), and subject area. These research directions can deepen our understanding of the conditions necessary for integrating DE education post pandemic. In addition, it will be useful to clarify whether DE and other forms of technology-mediated education—such as blended learning—should be considered as competitive, alternative or overlapping models. Finally, new directions of inquiry may focus also on the design of different kinds of DE or blended learning environments, based, for example, on problem-based learning, project-based learning, and/or knowledge building (e.g. Saputra et al, 2019; Author et al., 2024; Tan et al., 2021), in order to identify which theoretical model can better promote teacher’s acceptance of DE.

Declarations

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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.Integrating Generative AI with Open Educational Practices (OEP) in an Online Learning Environment: College Instructors' Perceptions, Potentials, and Challenges

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Abstract

This article explores open educational practices (OEPs) and generative artificial intelligence (AI) from college instructors' perspectives. The novelty of this study lies in bringing new insights by thoroughly examining the adoption of open educational resources (OERs) using generative AI in an online learning environment. Furthermore, it adds to the global conversation on OERs implementation in transitioning nations, emphasizing how OERs can democratize knowledge and enhance skill development in such environments. In terms of practical application, the study offers valuable insights to equip policymakers, educators, and institutions with the necessary information to address current challenges and devise effective strategies for integrating OER into OEPs. Investigating perceptions of combining generative AI tools with OERs can help instructors better plan activities that utilize these tools in the context of higher education. The present research considers four components of college instructors' perceptions of generative AI tools: efficiency, interaction, affect, and intention. A mixed-method research approach combines quantitative and qualitative methodologies with a questionnaire, focus groups, and semi-structured interviews. A total of 50 college instructors responded to the questionnaire; they teach different disciplines at Palestine Technical University-Kadoorie and used generative AI in their courses. The findings indicated significantly high perception scores for interaction, medium scores for intention and efficiency, and low scores for affect. Content creation and personalization emerged as a main theme in qualitative findings. Themes for challenges that emerged include data privacy, transparency, and ethical use. It is recommended that practical approaches for responsibly integrating AI tools be implemented in educational settings, including robust data governance frameworks to safeguard privacy and regular audits of AI systems to detect and address biases.

Keywords: Generative artificial intelligence (AI), open educational resources (OERs), open educational practices (OEPs), online learning, perceptions, Palestine Technical University-Kadoorie (PTUK)

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Openness in education encompasses methods, educational resources, and a philosophical mindset that can bring about a transformation in teaching and learning. It is a dynamic idea influenced by the evolving requirements of different societies, cultures, locations, and economies, making a single definition problematic (Bozkurt, 2019). Many categories like OERs and OEPs have been investigated in the literature (Bozkurt, 2023a; Panke, 2024; Paskevicius & Irvine, 2019; Van Wyk et al., 2023). The literature underscores the importance of open processes involving the development, utilization, and acceptance of OERs within educational settings (Bozkurt et al., 2019). In this continually changing environment, OEPs have developed as an expression of open pedagogy aimed at empowering learners to collaboratively create course content (Wiley & Hilton, 2018). Open pedagogy transcends the mere utilization of OERs in classrooms towards the creation and dissemination of OERs among learners who actively participate in shaping their learning materials (Baran & AlZoubi, 2020). Generative artificial intelligence (AI) holds immense promise in data analysis, pattern recognition, and transformative opportunities for generating and managing OER content (Panke, 2024) by enabling customization to individual or local requirements and improved accessibility.

Although OERs have existed for more than twenty years, their widespread adoption has faced numerous challenges, including time required to find and adapt materials, quality and accuracy assurance issues, and a frequent lack of institutional incentives for instructors to use them (Han & Kumwenda, 2025). In contrast, since generative AI was unveiled in late 2022, it swiftly amassed a staggering 100 million users within two months (Mesko, 2023). Consequently, generative AI has emerged as a prominent subject in educational technology discussions (Panke, 2024).

The main objective of this article is to examine the influence of generative AI on the creation and utilization of OEPs. Perceptions of college instructors play a crucial role in the adoption of these tools in their teaching practices.

Literature Review

Generative Artificial Intelligence

Artificial Intelligence (AI) has revolutionized online learning, with capabilities like automatic learner data analysis and personalized learning process (Willis, 2023). AI is a broad concept encompassing various technologies and approaches, including machine learning, natural language processing, data mining, neural networks, and algorithms. AI and machine learning are frequently linked together. Machine learning serves as a technique within AI, utilized for tasks like supervised and unsupervised classification and profiling. For instance, it can be applied to predict outcomes such as student dropout rates or admission probabilities or to detect themes within written assignments (Zawacki-Richter et al., 2019).

Baker and Smith (2019) offer a broad definition of AI, framing it as computer systems performing cognitive tasks akin to human minds, particularly in learning and problem solving. This expansive definition encompasses various technologies and methodologies, including machine learning, Natural Language Processing (NLP), data mining, neural networks, and diverse algorithms (Bozkurt, 2023a).

In discussions about the future product of emerging open pedagogy and generative AI, Tlili and Burgos (2022) highlight AI's potential to significantly enhance both teaching and learning experiences based on OEPs with different layers. For example, the first layer

involves the mindset and personality of learners and educators; the second involves changing the design from static to dynamic; the third mandates that the AI algorithm itself should be open; the fourth addresses the necessary competencies educators and learners must develop; and the fifth is a policy layer to protect all previous ones. This literature review section summarizes established principles of open pedagogy ideas when adopting generative AI.

While the body of literature regarding OEPs is limited, its richness in comprehending and valuing emerging technologies positions it as a suitable framework for the present investigation. Ultimately, the exploration of educators' perceptions on integrating generative AI with OEPs and investigating potentials and challenges, is essential and holds a significant promise in this field.

Open Educational Practices (OEPs)

The open education movement aims to democratize education by eliminating barriers and by leveraging the advantages of openness, an approach that has significantly influenced higher education (Mojtahedzadeh et al., 2024). Within this movement, OEPs have emerged as a central concept. While OEPs are closely associated with OERs, they represent a broader shift in pedagogical approach. As Bozkurt et al. (2019) explained, OEPs originated from the examination of OERs and are often discussed in the context of removing obstacles to their creation, use, and adoption. Essentially, OERs are the open content while OEPs are the open practices that use that content to empower learners.

The literature outlines two primary strands of OEPs. The first, and most common, focuses on practices directly related to OERs, such as creating, adapting, and using open resources (Koseoglu & Bozkurt, 2018). The second encompasses a wider vision of openness, including open pedagogy, open learning, and open teaching. Research into these practices has identified significant advantages, including enhanced accessibility, reduced student costs, and improved opportunities for collaborative learning and content customization (Adil et al., 2024). However, major challenges persist, such as quality assurance, sustainability concerns, a lack of institutional support, and technological barriers. This highlights a need for better strategies to support educators in adopting OEPs effectively.

Further, Paskevicius and Irvine (2019) noted that OEPs are being utilized within higher education, proposing that OEPs signify an evolving approach to learning design. They found that faculty members showed a growing interest in employing open strategies and technologies to facilitate active learning experiences, showcase learners' work in real-time, facilitate formative feedback and peer review, and foster community engagement within coursework. Hence, open pedagogy, or OEPs, involves utilizing OERs to aid learning, as well as openly sharing teaching methods to enhance education and training across institutional, professional, and individual levels (Maultsaid & Harris, 2023). Some studies (Khan et al., 2024; Tamoliūnė et al., 2024) investigated the use of OERs in an online environment and found that OERs offer significant and unique advantages for an online learning environment by providing no-cost or low-cost access and opportunities for creating, sharing, and using educational resources.

Open Pedagogy is an educational method that has been conceptualized in various ways. At its core, it encompasses teaching and learning methods facilitated by the open licensing of content (Werth & Williams, 2022) along with a philosophical and practical commitment to education that prioritizes accessibility and learner empowerment. A study conducted by Chen and Henricks (2023) reported that students recognized numerous

advantages of open pedagogy tasks, such as exerting greater effort to generate superior-quality output and heightened focus on the coherence of their writing. Students noted an augmented sense of accountability as creators of knowledge, evidenced by meticulous attention to the precision of their work and the credibility of their sources. Indeed, the term “open pedagogy” has been in use for several years. Bloom (2019) defined open pedagogy as a wider approach to transforming the educational journey to be more significant by utilizing the freedoms of open content to engage students in a more interactive learning process through tasks involving curation and remixing.

Generative AI in Education

Both scholarly reviews of literature and anecdotal evidence related to the use of AI in higher education are on the rise. Studies by Asaad (2024) and Sarwanti et al. (2024) have shown the significant role of generative AI in supporting college instructors, researchers, and students in higher education institutions. Additionally, recent studies have shown the potential of using generative AI in enhancing various aspects of education including improving personalized learning by supporting individual learning journeys, increasing productivity, generating ideas, and improving the efficiency of academic work (Bae et al., 2024; Chan et al., 2024; Karataş et al., 2024; Sarwanti et al., 2024).

Also, it is crucial to recognize potential issues associated with integrating AI tools in the classroom. For example, the use of an AI-powered platform can support collaborative learning by promoting increased engagement, idea-sharing, and collective problem solving among students. When students received feedback from the AI, some were able to ask follow-up questions via the chatbot (Ho, 2024).

A study conducted by Bozkurt et al. (2023b) investigated a variety of uses of generative AI in education and indicated that educators use AI to support learning. For example, educators employ AI to broaden and enrich traditional teaching methods, incorporating AI to bolster collaborative learning, demonstrate methodologies, and facilitate visualization. A noticeable shift towards novel applications of AI, such as employing AI tools to simulate a beginner learner, positions students as educators responsible for instructing the novice learner. In this regard, Baidoo-Anu and Ansah (2023) noted that generative AI offers incredible adaptability, spanning from generating language to producing images, and boasts diverse applications across various sectors, including education. One of its most compelling aspects is its capacity to revolutionize learning encounters. Through harnessing AI-powered content creation, educators can fashion engaging and interactive educational materials customized to the unique needs of each learner. Whether through adaptive learning platforms, personalized instructional guides, or virtual simulations, generative AI enables educators to design dynamic educational experiences that accommodate various learning styles and preferences. Furthermore, by generating authentic assessment tasks and feedback mechanisms (Cacho, 2024), AI enhances the assessment process by furnishing timely insights into students' progress and levels of proficiency. A recent study by Kurtz et al. (2024) outlined how generative AI presents significant prospects for enhancing students' learning journeys by creating customized learning environments that cater to their educational requirements. These advancements empower collaborative knowledge construction, nurturing an inclusive and interactive educational atmosphere. By offering personalized learning experiences coupled with immediate feedback, generative AI possesses the potential to enhance educational achievements and prepare students for upcoming career demands. Additionally, it aims to democratize education by offering adaptable, scalable solutions that accommodate diverse learning preferences and speeds.

Integration of Generative AI and OEP

The expansive influence of AI has a profound impact on OEPs. Mills et al. (2023) examined how to invest in OEP in the era of generative AI, highlighting practices that involve engaging with online communities to crowdsource and curate learning materials across institutional boundaries. A core tenet of this approach is that by openly licensing resources for reuse and adaptation, educators can build upon existing work and collaborate with students to develop emergent, student-centered learning approaches. Generative AI is a powerful catalyst for these OEPs. For example, AI can directly enhance OERs across their entire lifecycle. Building on this, Ossiannilsson et al. (2024) reported that AI can enhance OER production (e.g., by generating initial drafts of text, images, or quiz questions), access (e.g., through AI-powered search and recommendation systems that connect learners to relevant OER), reuse and adaptation (e.g., by instantly translating content, lowering its reading level, or converting a text into a lesson plan), and redistribution (e.g., by helping to tag and categorize OER for wider dissemination in repositories). Also, generative AI can help address issues within OEPs by promoting openness and ethical use. Its generative capabilities and human-like language proficiency enable the creation of resources such as course materials, activities, examples, questions, assessments, and learning outcomes in the context of OEP. Through machine learning and deep learning, generative AI can improve the discoverability and accessibility of open resources by enhancing metadata quality (Aksoy & Kursun, 2024). Panke (2024) investigated the convergence of OER and artificial intelligence (AI), with a specific focus on open pedagogy applications. Panke (2024) also explored course concepts and provided firsthand insights into crafting and executing student-oriented, sustainable assignments by integrating AI tools into open-access book projects. Meanwhile, Panke (2024) expressed fears of generative AI tools such as ChatGPT where students can easily create paragraphs and summarize entire essays, potentially compromising academic integrity by bypassing the learning process. Additionally, Mills et al. (2023) proposed that teachers should teach about generative AI using a set of OEPs, inspired by OERs. These practices include shifting toward online communities across institutional boundaries.

Bozkurt (2023a) critically examined the shift from human-generated to AI-generated content, marking a new era in education, especially regarding OERs and OEPs. The research investigated the potential of generative AI in OERs and OEPs, encompassing tasks like automatic content creation, resource curation, material updates, collaborative creation, and the facilitation of collaborative learning settings. Nevertheless, it highlighted the need to address challenges including quality and reliability of AI-generated content, data privacy concerns, and equitable access to AI technologies. Moreover, because generative AI introduces challenges like data privacy, security concerns, copyright issues, biased outputs, and the risk of generating misinformation, Bozkurt (2023a) emphasized the need for a balanced approach that considers both the advantages and risks of integrating generative AI into OEP. Ongoing research and development in applying these technologies to education are crucial for shaping the future of learning (Aksoy & Kursun, 2024).

Theoretical Framework: Community of Inquiry (CoI)

Community of Inquiry (CoI) provides a good framework for this study since it focuses on understanding and designing meaningful online experiences (Garrison et al., 2000). The CoI framework states that learning occurs by three intersecting components: social presence which relates to interaction; cognitive presence, which relates to meaning construction through dialogue; and teaching presence, which relates to the facilitation of the educational experience (Fiok, 2020). The CoI framework informs this study since generative AI is not merely a tool but a transformative agent that interacts with all three

components. It can enhance teaching presence by helping instructors in the design of OERs. It influences social presence by serving as a conversational partner for both instructors and students. Additionally, it impacts cognitive presence by offering a variety of raw material for synthesis and co-construction (Mielikäinen & Viippola, 2023). This framework informed the study's design since generative AI is not merely a content creation tool, but a dynamic engine for personalization within OEPs. It guided the researcher to investigate how AI-driven algorithms could analyze learner data to customize educational resources and assessments in an open education environment. Therefore, this framework is robust in analyzing instructors' perceptions: efficiency and intention (teaching presence), interaction (social presence), and affect (comfort with the three components). It is also useful for analyzing the potentials and challenges of integrating generative AI into OEP.

In conclusion, although generative AI tools show great promise in enhancing learning experiences, concerns remain regarding accuracy, potential over-reliance, and unclear AI usage policies. Current research lacks a comprehensive exploration of AI-driven environments in open education, particularly from the viewpoints of college instructors. Thus, further studies are necessary to fully understand generative AI integration in open educational contexts. We provide a thorough understanding of this topic by considering the perspectives of college instructors. While considerable research has been conducted on generative AI such as ChatGPT, investigations have not specifically addressed its integration within the context of open distance e-learning (ODEL) environments; this gap in the literature sparked the author's interest to examine this phenomenon within an Open education. This study explores the perspectives of educators regarding the use of generative AI tools within open pedagogy aiming to address the following questions:

1. What are college instructors' perceptions of integrating generative AI tools with OERs in their teaching?
2. What are the potentials of integrating generative AI with OEPs from college instructors' perspectives?
3. What are the challenges of integrating generative AI with OEPs from college instructors' perspectives?

Methodology

A convergent mixed-methods design was conducted to provide a comprehensive understanding of the study problem (Creswell & Clark, 2017). This approach involved collecting quantitative and qualitative data in sequence but for complementary purposes. The quantitative tool addressed college instructors' perceptions (RQ1), while the concurrent qualitative tools of focus groups and interviews explored the underlying potentials and challenges (RQ2 & RQ3) of integrating generative AI with OEP. The findings were integrated during the interpretation phase to develop a holistic understanding of the phenomenon. Quantitative findings were used to provide context for qualitative data, allowing for a deeper assessment of the potential and challenges. The research began with a descriptive quantitative phase, using a questionnaire for college instructors, followed by a phenomenological qualitative phase to describe the experiences of instructors. A qualitative design with a phenomenological approach was conducted to gather information for qualitative data. A phenomenological study is conducted to investigate specific lived experiences of college instructors who integrate generative AI tools into their OEPs.

A qualitative research approach, specifically using the inductive coding method, was utilized to analyze data. A qualitative study was also selected because it is best suited to capture the complex and nuanced aspects of users' reactions and responses to new technologies, trends, and phenomena (Blandford et al., 2016; Mogavi et al., 2024). The inductive method is particularly appropriate for this study due to the apparent lack of prior empirical research on user experiences related to the use of generative AI and OER in an online learning environment. Moreover, the inductive coding approach allows the researcher to develop themes from the data without preconceived notions or prior assumptions (Blandford et al., 2016; Mogavi et al., 2024).

Semi-structured interviews and focus groups with 21 participants were performed with college instructors who use generative AI and OERs in their online teaching via Zoom. These participants were selected based on their expertise in generative AI in their educational practices in online learning.

Participants

Participants who responded to the questionnaire are shown in Table 1.

Table 1

<i>Respondents' Characteristics</i>	Category	Number	Proportion
Variable			
Gender	Male	24	48%
	Female	26	52%
Teaching experience	5-10	10	20%
	11-15	17	34%
	>16	23	46%
Technical skills	Excellent	14	44%
	V.Good	22	28%
Academic rank	Good	14	28%
	Professor	6	24%
	Associate professor	18	18%
	Assistant professor	16	20%
	Lecturer	12	24%
Specialization	Engineering	9	18%
	Applied Sciences	12	24%
	Business & Economics	10	20%
	Agricultural Science and Technology	8	16%
	Arts and Educational Sciences	11	22%

Table 2*Participants' Characteristics of the Interviews and Focus Groups*

Instructor	Gender	Years of Experience	Department	Length of generative AI Usage
Instructor1	Female	7	Business Administration	3 months
Instructor2	Female	20	Economics	3 months
Instructor3	Female	7	Technology Education	7 months
Instructor4	Female	13	Math	4 months
Instructor5	Male	5	Computer Engineering	7 months
Instructor6	Male	14	English language	7 months
Instructor7	Male	20	Physics	2 months
Instructor8	Female	13	Technology Education	2 months
Instructor9	Male	17	Electric Engineering	7 months
Instructor10	Male	20	English	7 months
Instructor11	Male	12	Electric Engineering	6 months
Instructor12	Female	5	Chemistry	7 months
Instructor13	Female	13	Applied Biology	9 months
Instructor14	Female	9	Physics	7 months
Instructor15	Female	10	Graphic design	5 months
Instructor16	Male	11	Chemistry	4 months
Instructor17	Male	10	Arabic language	2 months
Instructor18	Male	30	Arabic language	3 months
Instructor19	Female	7	Teacher certification	2 months
Instructor20	Female	13	Information Technology	6 months
Instructor21	Female	7	Information Technology	5 months

Data Collection Tools

Quantitative data were gathered using a pre-existing questionnaire based on Daher and Hussein (2024) which assessed four aspects of perceptions toward generative AI: efficiency, interaction, affect, and intention. The questionnaire was adapted to the context of the study by combining generative AI and OEPs as attached in Appendix A. It includes four dimensions of perceptions according to Shoufan's (2023) study which found that perceptions of AI include efficiency, interaction, affect, and intention. Efficiency is related to understanding the concepts while performing tasks with generative AI such as planning lessons, assessing students, and professional development. The interaction dimension is related to the social aspect associated with AI-human interactions. Generative AI tools are specifically designed for conversational usage that imitates human-like responses by providing users with information and knowledge. Confidence to work with generative AI bots is related to the emotional aspect, self-confidence, interest, and motivation affect users' goal-seeking, and developing interest in creating lessons, and it decreases users' anxiety. The intention to use generative AI is related to assisting in problem-solving and assisting in research.

For the reliability of the questionnaire, Cronbach's alpha was computed, resulting in values of 0.748 for efficiency, 0.791 for interaction, 0.727 for affect, and 0.793 for intention, confirming the reliability of the questionnaire. Additionally, Pearson correlation between the items of each scale and the entire scale ranged from 0.651 to 0.842, demonstrating the validity of the four scales. Pearson correlation between each scale dimension and the overall questionnaire yielded values between 0.628 and 0.753.

To gather qualitative data on participants' experiences with generative AI, both focus group sessions and semi-structured interviews were employed. The semi-structured interviews aimed to elicit comprehensive responses to the following research questions:

1. How does generative AI influence open educational practices in your classroom?
2. What are the perspectives of college instructors toward generative AI when using open educational practices?
3. What challenges do college instructors encounter when generating AI in OEP?

Focus group sessions were conducted to collect qualitative data. These sessions, each comprising eight to ten college instructors, were held prior to the semi-structured interviews. Participants were selected based on familiarity with OEP and generative AI. The 120-minute sessions, accommodating 21 participants, were conducted both via Zoom and in-person. Participants' consent was obtained for recording the sessions. Privacy was ensured with participants' names undisclosed and their contact information securely stored.

The focus group discussions were guided by six open-ended research questions, derived from a literature review and reviewed by field specialists. These questions gauged participants' opinions on generative AI with OEP. Questions are listed below:

1. Describe your experience using generative AI tools in your teaching practice, particularly in the context of creating or using (OERs)?
2. In what ways, if any, do you feel generative AI has the potential to transform (OEPs) for you and your students?
3. How does generative AI influence your teaching practices?
4. What specific challenges or barriers have you encountered when trying to integrate generative AI into your open pedagogical approaches?
5. How does using generative AI influence your ethical responsibility as an educator practicing open pedagogy?
6. Please provide an example of a successful instance where you combined generative AI with an OEP. What made it work?

Semi-structured interviews aimed to gather detailed insights into participants' teaching experiences with generative AI. Semi-structured online interviews, lasting 25-40 minutes, were conducted with 21 college instructors who volunteered after focus group sessions. The interviews, conducted via Zoom, allowed participants to reflect on their experiences and offer feedback on the topic.

Participants for this phenomenological study were chosen based on their specific experiences with generative AI and their ability to articulate detailed descriptions of their experiences. Overall, these qualitative methods provided rich insights into participants' experiences, offering valuable information for understanding their perspectives.

Data Analysis

This study employed a phenomenological approach to explore the experiences of faculty members who utilize generative AI and how that might influence open pedagogy. Data collection involved verbatim transcriptions of both focus group discussions and individual interviews. The primary source of information was derived from these discussions and interviews, designed to uncover key themes and categories related to perspectives and obstacles to integrating generative AI with open pedagogy. Participants were encouraged to visually demonstrate their explanations as these interactions were recorded in both video and audio formats.

A content analysis of the semi-structured interviews and focus group transcripts was conducted by using the inductive method. The process involved abstracting and grouping materials to facilitate inductive reasoning in response to the research questions. Inductive analysis was employed to extract emerging themes from participant responses. In this analysis, coding data and categorizing relevant segments into categories and subcategories was done through an iterative process (Vears & Gillam, 2022). This involved multiple data readings, coding pertinent portions, and grouping similar codes into broader themes or categories (Lovrić et al., 2020; Daher & Hussein, 2024).

Given the inclusion of multiple focus groups, constant comparison analysis proved suitable for data examination, enabling the assessment of both within-group saturation and overall saturation. Data coding followed Creswell's six-step approach, which involved transcription and organization of data, initial analysis to grasp the essence of ideas, statement coding with segment and text data insertion, and code categorization and labeling, culminating in a discussion of themes.

Trustworthiness

To ensure the credibility of the qualitative data gathered from focus group sessions and semi-structured interviews, various techniques were employed. Credibility was established by cross-referencing data from multiple sources, such as interviews and focus groups. Furthermore, member checking was conducted, where participants were consulted later to validate the findings. For dependability, a code and recode strategy was implemented, with data independently coded by the researcher and another specialist, followed by discussions to ensure consistency in analytical approaches. Transferability was addressed by providing a comprehensive depiction of the study's context, enabling readers to assess the applicability of the findings to their situations. Confirmability was maintained by meticulously documenting the procedures for data verification throughout the study, ensuring that the conclusions were derived directly from participants' accounts rather than influenced by researcher biases.

Findings

Perceptions of Integrating Generative AI with OEP

For the first question of this study (“What are college instructors' perceptions of integrating generative AI tools with OER in their teaching?”), the normality of scores for each component of perceptions was analyzed. The Kolmogorov-Smirnov test results indicated that college instructors' perception scores were normally distributed ($p > 0.05$). Additionally, an inspection of boxplots revealed no outliers in the data. To determine the level of each component of college instructor's perceptions, the following ranges were used: .8-1.8 for very low, 1.9-2.6 for low, and 2.7–3.4 for medium, 3.5-4.2 for high, 4.3-5 very high. These intervals were derived from the calculation $(5-1)/5 = .8$, representing the length of each level. To verify the significance of each perception component's level, a one-sample t-test was conducted, as the scores for each scale were normally distributed as shown in Table 3.

Table 3

One-Sample t-test of Perceptions of College

Instructors of Integrating Generative AI with OEP

Test Value = 2.6							
Component	Mean	T	Df	p	SD	95% CI	
						Lower	Upper
Affect	2.7072	1.791	49	.079	1.02913	-.0380	.6620
Intention	3.3440	-.405	49	.006	.73406	-.3099	.2059
Efficiency	4.2300	7.167	49	.000	1.94362	.5354	.9526
Interaction	2.9120	2.656	49	.011	1.23166	.1776	1.2824

The result in table (3) show that the mean score for affect ($M = 2.71$) was not significantly different from the test value, $p = .079$, while the mean score for intention ($M = 3.34$) is significantly different from the test value, $p = .006$. Mean score for efficiency and interaction is ($M = 4.230$) and ($M = 2.656$) respectively. These results show that instructors who recognize the potential of generative AI are still grappling with its and hold mixed emotions about it. Crucially, they see enough potential to interact with generative AI.

Potentials of Integrating Generative AI with OEP

For the second question (“What are the potentials of integrating generative AI with OEP from college instructors' perspectives?”), two themes were considered: content creation and personalization, and supporting inclusive education.

Content Co-Creation and Personalization

Content Co-Creation by Instructors

Generative AI could empower instructors to create OER, like H5P's Falcon, which uses AI to transform existing static content (documents, video, or audio) into interactive, shareable content as OER in an online environment. A significant majority of participants

(57%) commented that generative AI is essential for supporting effective use of OERs. This essentiality stems from AI's ability to solve some persistent practical challenges in OER adoption like time required to locate relevant materials and curating content from OER based on specific learning objectives.

Instructor 3 mentioned, “Falcon analyzes the source file, for example, a video, transcribes it into text, extracts the main concepts, and generates new interactive content such as assessment tests or a glossary of terms that I can reuse while I am teaching online.”

Content Co-Creation by Students

Generative AI can help the student create and publish OER right with open-licensed projects, so instructors can teach students how to use AI to generate public domain projects.

Instructor 8 mentioned

So we do not just have to change our thinking a bit about AI not that students are just going to use it to plagiarize all day when they use it online, but you can get students to create AI online-based projects on your instruction like a project and when they create something because it is AI generated it's going to have to be published as an open domain product.

Instructor 5 affirmed that “Students can also prove their knowledge and skills by showing their AI projects when utilizing OER resources to a graduate school or potential employer so prompt engineering is a very important skill today.” From these two comments, instructors let students create AI-online based projects to enhance students’ AI literacy and to teach them to avoid passively accepting AI’s output, instead focusing on the process and not the final product. The learning objective is to engage in critical interaction with the technology. Instructors also use a powerful strategy by asking students to publish their projects online to mitigate plagiarism and ensure transparency which raises AAAI ethical awareness among students.

Development of New Skills

On both sides of the learning process, it is necessary to develop new skills; students must cultivate the fundamental skills that will enable them to exploit the potential of AI and teachers must update their skills for the creative and educational use of tools such as ChatGPT and OER in their teaching practices.

Utilizing open educational resources (OERs) that are produced by generative AI aligns well with our goals, enabling us to employ collaborative, renewable, reusable, and authentic assignments to bolster our students' roles as both learners and content creators. With numerous platforms and resources available, there's no need to start from scratch; instead, we can work more efficiently by leveraging existing tools and knowledge. (Instructor 12)

It seems that the use of generative AI in utilizing OEPs by generating OERs (e.g., draft texts, questions, case studies) indirectly produces or enables new OEPs by providing the foundational material for renewable student-led projects.

Moving from “Static” to Interactive Content

Generative AI helps to generate interactive online content much quicker than in the past. Many participants mentioned that they have always been bothered by the fact that the

OER tends to be dominated by static materials, much of which is stuff that we could have developed in the late 20th century. And there is very little of it that is very native to the digital environment.

Instructor 3 said

Creating quality interactive learning content takes time and expertise. And that was always a major stumbling block for us as college instructors. But with generative AI, using the right methodology, you can eliminate weeks of work to make OER that you have more interactive and engaging for your students.

Time and Effort Saving

Generative AI appears to save time and effort for OER content creation. Instructor 13 mentioned that

If I was creating even a short learning simulation if I wanted to do the first iteration of it. It would probably take me a couple of weeks to plan out the scenarios, the branches, and the feedback, to say nothing of finding the right images that were openly available. It was very time-consuming, and that's certainly not my full-time job. But using a reasonably robust AI tool, I can now create a working prototype within about a day if I'm disciplined. And that's an enormous leap in terms of the time.

Instructor 19 added that

I think the time issue was the biggest obstacle for creating, modifying, or adapting a lot of quality interactive OER. I think generative AI tools have now removed that wall. And I think we should make people aware of that, that we can now do things that we've never done before. So, that's, to me, the probably most exciting part of the introduction of generative AI to OER.

Personalized Learning Paths

Generative AI can analyze learners' performance and create a tailored learning path for each student. This will ensure that learners focus on the competencies they need to strengthen and learn efficiently. Generative AI offers content suggestions that match their needs.

The possibilities impact of generative AI's specifically on OER are quite compelling. The advantages of adaptive learning environments, the adaptation of the pace of content delivery and task complexity in real-time, offering a genuinely personalized learning encounter that significantly boosts learner involvement and retention.
(Instructor 7)

It seems that adaptive systems can recognize when a learner is facing challenges and provide additional support or simplify the material, just as they can present more advanced materials when a learner is excelling. This adaptability not only optimizes learning efficiency but also sustains learner motivation and engagement, crucial elements for successful educational outcomes.

Collaboration

Generative AI collaborative platforms provide college instructors with significant potential to enhance OER sharing, communication, and collaboration. This was evident from the participant's responses. Instructor 2 mentioned that “even though I have been using generative AI tools for two months, it made my online teaching practices easier by offering more collaboration with my colleagues.” This reveals that generative (AI) appears to facilitate collegial collaboration by offering tools for co-creating and curating and contextualizing existing open resources and generating consistent assessment frameworks. Generative (AI) can generate a curated list of resources to initiate collaborative projects.

Supporting Inclusive Education

Combining generative AI with OEP plays a vital role in promoting inclusivity in specialized fields such as chemistry, physics, and biology or other professions requiring tailored educational approaches. By eliminating learning barriers, AI technologies enable personalized education plans that cater to learners with diverse educational backgrounds and abilities. For example, in chemistry education, generative AI can simulate complex reactions for students, providing them with hands-on experience in a controlled, virtual environment tailored to their learning pace and style.

Instructor 11 said, “The availability of educational resources in different languages is a key factor of inclusion and open access.”

Although in general, ChatGPT works better in English due to the availability of a larger database to train the systems, its potential for all other minor languages is still enormous.

Examples of AI-driven solutions in specialized learning environments include platforms that adapt teaching methods based on the learner's retention rate and feedback. For individuals with specific learning disabilities, AI systems can adjust content delivery to meet their unique needs, ensuring that each learner can achieve their potential regardless of their challenges. This level of personalization not only enhances learning outcomes but also ensures that education is accessible to a wider audience, fostering a more inclusive educational landscape.

Equitable Teaching Practices

Instructors noted that generative AI with OEP can provide universal access for all students. As Instructor 17 noted, “Integrating OER with generative AI tools helps to reach many learners based on their language preference because you can get for example chat GPT to speak to in Arabic or English or any language that you want.”

Universal access supports equity-based teaching and learning. Combining OER with generative AI considers students' learning needs and preferences. Instructor 18 confirmed that “Because generative AI can do that much better than us it can remember what the student said what the student does, hence I could say that generative AI tools enhance OEP online.” Generative AI promotes equitable teaching practices and adapts to the learner so it is a form of adaptive learning it can also work as a virtual facilitator so if we know that Chat GPT will soon be embedded.

Improving Student Engagement

Combining generative AI with OEP is revolutionizing content delivery for teachers by creating and adapting interactive and immersive learning resources such as simulations,

virtual labs, and gamified elements. These tools enhance engagement and memorability by enabling learners to experiment in a risk-free setting and apply concepts in virtual scenarios before tackling real-world applications. The interactive nature of this content, facilitated by AI, can lead to increased engagement levels and deeper comprehension of complex subjects.

Instructor 2 commented that “AI-regenerated OER caters to diverse learning styles, enhancing the accessibility of learning materials. Visual learners benefit from rich graphics and videos, auditory learners from podcasts and simulated dialogues, and kinesthetic learners from interactive and tactile interfaces.”

By offering a range of content types, generative AI ensures that learning is not only more effective but also more inclusive, accommodating the preferences and requirements of all learners, thus democratizing education.

OER Translation and Localization

Participants reported that integrating generative AI with OER was advantageous for them as well as their students, since it translates and localizes knowledge. Many participants reported that generative AI can translate OER into multiple languages which supports multilingual education and localization.

Instructor 7 mentioned that “generative AI can translate massive OER into multiple languages, which makes and supports high-quality education and making resources accessible to English as second language learners in different regions.”

Instructor 5 commented that “Generative AI tools like gamma can adapt and localize instructional content to fit cultural contexts of my students, which ensures that instructional materials are relevant and relatable to students from diverse cultural backgrounds and contexts.”

For the third research question (“What are the challenges of integrating generative AI with OEP from college instructors’ perspectives two themes emerged: data privacy and transparency.

Data Privacy

As personalized learning necessitates the collection and analysis of extensive personal data, data privacy is paramount. Ensuring the secure handling of this data and maintaining privacy is crucial for maintaining trust.

Additionally, the potential for bias in AI algorithms can result in unfair advantages or disadvantages for certain learner groups, requiring rigorous testing and calibration to ensure fairness and transparency. “In fact, earlier today, a colleague was talking about using Claude AI to combine and remix existing assignments in new ways. So, for people who have been doing OER work around remixing. It is a great tool for really coming up with innovative new models of existing materials. (Instructor 1)

Transparency and Trust

Open pedagogy advocates for instructors to empower students to become creators rather than mere consumers. This approach enables students to engage in curating and crafting content, fostering their identity as active contributors to the public sphere of ideas. However, challenges such as transparency were noted as potential hurdles to this creative process. I'm still excited, but I also have, the concerns are more in the

foreground, and there are some things that we haven't yet figured out and, you know, the copyright issues! And there are some real concerns around source attribution and transparency around AI that I think that it'd be great to come up with some more systematic and clear kind of procedures for those. (Instructor 13)

Instructor 6 added that “An LLM can be an excellent help in defining the setting and structure of the papers, but students will still have to verify the sources, train themselves to decode the truth: activities that require information literacy skills, which is positive.”

Discussion

For the first question (“What are the perceptions of faculty members of integrating generative AI with OEPs?”), findings revealed that the average scores for intention and efficiency were notably medium, while the score for interaction to combine generative AI with OER was significantly higher. These results may reflect the nature of generative AI tools like AI bots.

For the medium intention scores, the use of generative AI with OER in higher education has not yet been fully integrated, and college instructors are still exploring and assessing their potential in this integration. This exploration may account for the medium levels of efficiency and low effect dimensions. For medium levels of efficiency, the use of generative AI with OER has not yet been established as a tool in higher education and the ability of these tools to save time and resources is still not within its capabilities. Low effect could be due to lack of using generative AI with OER which creates fewer emotions during the exploratory phase rather than the adoptive phase. Nonetheless, college instructors are keen to use generative AI with OERs to enhance OEPs in their teaching practices, likely due to the perceived benefits and the continuous improvements in these technologies. The medium efficiency scores were reported previously by Ossiannilsson et al. (2024) who reported that harnessing the power of AI to implement OER promotes efficiency by giving users the opportunity to brainstorm, summarize information, enhance discussions, and promote learning pathways. Moreover, while Mican et al. (2023) found a moderate to high value for the behavioral intention to use AI, they attributed this variance to determinant factors like facilitating conditions, habit, and social influence, and its moderators' knowledge of the English language, study domain, and gender. Despite the moderate level of college instructors' perceptions of using generative AI with OER, their intention to use them remains high, indicating that additional factors may influence the evolving capabilities of AI bots in educational settings. Moreover, some demographic variables (interview, participants' field of expertise and length of AI usage) show that they were not all AI experts. Their experience with generative AI ranged from 2 to 9 months, which indicates that they were largely in the early adoption phase. This might explain the medium efficiency and intention scores since they were still exploring the usage of generative AI.

In practical terms, this indicates that while instructors recognize generative AI as a powerful asset, they are still not yet fully committed to integrating it into their regular teaching with OERs. They may be trying to practice with generative AI for specific tasks like brainstorming OER topics but have not yet integrated it into their core instructional design. This limited usage could be due to accuracy concerns of AI-generated content, the time and effort needed to edit the output, and a lack of clear institutional policies. Hence, the medium efficiency score suggests that the promised benefits of timesaving are not yet a consistent reality for many instructors. Meanwhile, the significantly high score for interaction shows

that instructors highly perceive generative AI tools as very responsive and capable of facilitating dialogue. Instructors perceive AI tools as effective for interacting with educational content when creating questions from an OER textbook chapter, creating multiple explanations of complex concepts to meet students' diverse needs, and curating large number of open-access resources. The high interaction score shows the strengths of generative AI, like its ability to generate customized interactive content which aligns well with the dynamic nature of OEPs.

For the second question, two themes (content co-creation and personalization) emerged for possibilities for using generative AI in OEPs. Generative AI is useful as a support for creative unlocking individual brainstorming contexts. The dialogue with the chatbot can provide a starting point for developing unpublished documents by students, who often feel immobilized in front of a blank page. For example, empirical observations suggest that although ChatGPT generates content of moderate quality with limited creativity, this limitation can function as a cognitive scaffold, prompting students to engage in comparative self-assessment and strive for superior outputs. A study by Bozkurt (2023c) confirmed that generative AI can be utilized in OERs and OEPs, including tasks like automatic content generation, resource curation, existing materials updates, co-creation facilitation, and collaborative learning assistance. Hence, it is critical to utilize the power of generative AI and use OERs and OEPs in an online learning environment by creating educational content which is important for both teachers and students. Generative AI tools seem to support the curation and creation of OERs, which offers a more dynamic and interactive online learning environment.

These capabilities directly enable the development of personalized learning paths. Instructors mentioned how generative AI could create different learning paths in the online environment according to data gathered by these systems. This finding is in line with Tlili and Burgos (2022) who reported that generative AI produces automatic and different learning and teaching paths for both learners and educators and facilitates the finding of adequate OERs for better OEPs in the learning and teaching outcomes according to the personality characteristics as well. Therefore, generative AI may provide dynamic OERs that can be customized and tailored to students' needs by making online learning more accessible. This is considered a pedagogical shift in online learning since educators can consider integrating generative AI tools into their teaching practices by fostering a more interactive and student-centered learning experience since an interactive online learning environment was a challenge for some educators.

This finding concurs with Tlili et al. (2021) who demonstrated how AI can facilitate the search for OERs through a sort of automatic tagging, solving the age-old problem of how teachers and students can find relevant open content quickly. In terms of access to education, generative AI can primarily be used to make OERs more accessible to students by, for example, creating translations of OERs in different languages or accessible versions for students with disabilities or adapting content to different socio-cultural contexts. This result could be explained as generative AI can make everything easier and solve some problems that underlie sharing, such as the scarcity of resources in minority languages. Meanwhile, it has some disadvantages like raising the barrier of trust, creating a world in which teachers have to look at themselves not only from colleagues who could use their resources. This is in line with Ossiannilsson's (2023) finding which recommended that the creation and distribution of openly licensed educational materials should be designed with universal accessibility in mind, to benefit students, educators, and researchers globally. Moreover, prioritizing the social, ethical, and moral aspects of learning and education is crucial for

advancing social justice, equality, human rights, prosperity, liberation, and growth in line with major global initiatives.

For the second theme, supporting inclusive education, generative AI leverages its extensive capabilities in data processing and pattern recognition, which supports transformative opportunities for generating and organizing OERs content. It enables adaptation to individual or local requirements and improves accessibility. This represents a chance for students to enhance productivity and foster creativity within open pedagogy and enduring assignments (Wiley & Hilton 2018). Moreover, Generative AI's extensive data-processing capabilities allow for the automatic adaptation of OERs to meet diverse learner requirements. This includes creating language translations, generating accessible versions for students with disabilities, and adapting content to various socio-cultural contexts (Ossiannilsson, 2023). By solving the perennial problem of locating relevant open content through automatic tagging and summarization (Tlili et al., 2021), AI significantly lowers barriers to access which enhances engagement of learners. Prioritizing these applications is crucial for aligning OEPs with global initiatives aimed at promoting equality, human rights, and inclusive growth. Moreover, themes also might be influenced by departments of instructors. For example, science-based departments frequently highlighted AI's usage for creating virtual labs and simulations, while instructors from language and social sciences department discussed its role in brainstorming, translation, and image usage.

For the third question of this study related to the challenges of generative AI integration with OEP, themes were found related to ethical issues like data privacy and transparency of resource production. It is enough to imagine a collection of OER whose resources are autonomously read, updated, and improved by AI to understand the legal and political implications, and it becomes important to ask who develops and controls these mechanisms to support quality (Kamalov et al., 2023).

Trust was also found to be an issue. For example, instructors do not trust the quality of the content produced by others, and at the same time they might not trust the use that others could make of them, the introduction of the magic machine capable of criticizing and improving the teachers' work (Tlili et al. 2021) could create a world in which the propensity to share decreases, rather than increases. In a collection of OER whose resources are autonomously read, updated, and improved by generative AI, it is still hard to understand the legal and political implications, and it becomes important to ask who develops and controls these mechanisms to support quality.

Further challenges reported in using generative AI to support OEP of copyright, privacy, and the use of personal data, for which most teachers are not ready (Tlili & Burgos, 2022). Hence for effective usage of generative AI in online learning while using OER and OEP, ethical use should be considered and generative AI should complement rather than replace online learning strategies.

In summary, generative AI is, and will be, increasingly capable of supporting teachers in all the typical activities of working with OERs: content creation, tagging, promotion of the same, cataloging, and modification, towards dynamic co-creation between teacher and AI (Bozkurt, 2023b).

Conclusion

Generative AI promises significant advancements that will further revolutionize personalized education. Predictive analytics, deeper customization, and even more immersive and interactive learning experiences are just a few areas where AI is expected to make substantial strides. As technology progresses, educators and institutions are urged to remain at the forefront of these developments, embracing new tools and methodologies to enhance educational delivery and outcomes. Generative AI can be utilized in OER and OEP, including tasks like automatically generating content, curating resources, updating existing materials, facilitating co-creation, and enabling collaborative learning.

The proactive integration of generative AI into educational strategies prepares learners for a rapidly changing world and ensures that education remains relevant, engaging, and inclusive. By staying abreast of AI trends and continuously adapting to technological advancements, educators can equip learners with the skills and knowledge necessary to thrive in the future, shaping a new era of education that is personalized, accessible, and effective.

Practical approaches are needed for responsibly integrating generative AI tools in educational settings, and incorporating AI ethics into the curriculum is essential. Integrating generative AI ethics in educational programs is crucial to expanding AI literacy and ensuring that the development and use of AI technologies are inclusive, addressing the issues of underrepresentation in terms of equity and quality (Salhab, 2024). Additionally, establishing an AI ethics code for higher education institutions, with clear guidelines and policies for responsible AI development and implementation, is necessary. Moreover, robust data governance frameworks to safeguard privacy and regular audits of AI systems to detect and address biases must be implemented. More specifically, an ethical AI data governance framework must ensure that educational institutions maintain transparency about how AI models are developed, trained, and delivered. A practical solution for achieving transparency could be the use of unbiased datasets that are fundamental to creating a transparent AI system. Regular evaluations should be conducted to ensure the data stay relevant, free of bias, and accurately represents diverse viewpoints. Furthermore, institutions must focus on bridging the digital divide by ensuring all learners have access to the necessary technology and infrastructure to benefit from AI-enhanced education. Moreover, an ethical data governance framework must include strategies and policies that guide the ethical development, use, deployment, and regulatory adherence of AI technologies within an educational institution. Personal and sensitive data must be treated with strict confidentiality and utilized solely for educational purposes. Additionally, educating students and staff on data privacy is essential. They should be informed about how their data is used and the protective measures in place. Such transparency fosters trust and ensures that everyone understands their data privacy rights. By tackling these challenges directly, educational institutions can harness the full potential of generative AI while upholding ethical standards and fostering an inclusive learning environment.

Like all research, this study has certain limitations that should be acknowledged. First, the sample was limited to Palestinian university instructors from a single institution, which may affect the generalizability of the results to other populations and settings. Furthermore, using self-reported data in the quantitative design could introduce social desirability bias, where participants may exaggerate positive behaviors or downplay negative ones, such as their perceptions of affect and intention domains to use generative AI in open teaching practices (Caputo, 2017). Another limitation stems from the study's cross-sectional design,

which only captures college instructor views and perceptions at a certain time (Bowen & Wiersema, 1999). Additionally, more cross-cultural comparisons should be made that would provide a clearer roadmap for advancing this field. The influence of demographic variables was not explored in this study and could be investigated in future studies.

Future Research

Providing a more comprehensive understanding of using generative AI in open education practice's role in higher education settings necessitates future research. Including college instructors' perceptions from a broader range of geographic locations and academic institution in future studies would improve the generalizability of the findings. Longitudinal studies could help track changes in college instructors' perceptions and behaviors over time, while employing a more balanced mixed-method approach, with in-depth qualitative interviews or focus groups, could offer richer insights into how college instructors incorporate generative AI into their open teaching practices.

Declarations

The author declares no conflicts of interest associated with this study. The authors declare no funding associated with this study. Permission to conduct research on human subjects was granted by the ethics board of the institution.

Data Availability

The datasets generated during and /or analyzed during our current study are available from the corresponding author on a reasonable request.

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Appendix A

Efficiency	1	Generative AI enables OEPs by solving pedagogical problems.
	2	Integrating generative AI with OERs is helpful and effective.
	3	Generative AI tools will really help students and instructors by providing a start point for renewable materials for open content.
	4	Integrating generative AI to assist in OEPs is helpful and effective for learning.
	5	Generative AI enables and scaffolds new forms of OEPs by providing the essential building blocks.
	6	Generative AI tools can process and analyze large amounts of data quickly and accurately that support OERs.
	7	Generative AI can help instructors quickly generate frameworks for student projects to be published as OERs.
	8	Generative AI tools are useful to create different resources for different disciplines.
		Integrating generative AI enables innovative OEPs.
Interaction	1	It feels like having a smart friend who you can ask anything when using generative AI to adapt OERs.
	2	Using Generative AI with OER tools makes a human-like, friendly impression.
	3	You can ask follow-up questions when you modify and adapt OERs and the generative AI tool stays in the conversation.
	4	The interaction with generative AI while co-creating of OER is engaging.
	5	Generative AI tools can understand and respond to my queries effectively while creating and curating OERs.
	6	It is easy to interact with open content that was designed using generative AI.
	7	Generative AI tools are clear, which helps me engage in open educational practices
	8	The answers generated by generative AI tools when creating open content are well-structured.

	9 Generative AI tools can generate human-like responses that support open pedagogy.
Effect	1 I find it very motivating to integrate generative AI tools to support OEPs.
	2 I am amazed by the capability of integrating generative AI with OERs.
	3 I find it very interesting to integrate generative AI with OERs.
	4 I feel optimistic about the potential of generative AI tools in supporting OEPs.
	5 I feel confident using generative AI tools to adapt OERs for my academic work.
	6 Working with generative AI tools reduces my anxiety in my profession.
	7 I am comfortable using generative AI as part of my teaching practices.
Intention	1 I intend to use generative AI with OERs tools in my teaching.
	2 I plan to continue using generative AI tools to assist with OEPs.

Leadership in Song: Developing Leadership Practices Using Music in an Online Course

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Abstract

“Leadership in Song: Developing Collaboration, Community, and Leadership Practices through Music in an Online Course,” is an introductory exercise in an online synchronous educational leadership class that outlines how music can be used as a pedagogical tool to create a cognitive collaborative community of inquiry that fosters a) reflection, b) collaboration, c) value of different leadership practices and d) affective connections to the assignment. Additionally, this assignment provides a transferable activity that school leaders can modify for use with various stakeholders in their schools. Significantly, this assignment underscores how music, an often-underutilized pedagogical tool in academia, creates a reflective, collaborative, engaging, relevant, interactive virtual experience for educational leadership students in an online environment. I applied a series of steps traditional to qualitative analysis such as open and axial coding, noting patterns, and maintaining a chain of evidence; students reported what they valued and learned from the assignment and emphasized how this assignment can be used to enhance collaboration and self-reflection, revise initial ideas, and understand different leadership perspectives. This lesson can be used in online settings as a team-building exercise in a classroom or with a leadership team at the beginning of the school year to help faculty and staff form a community around the school’s goal and mission.

Keywords: Developing leadership practices, collaboration in online learning, use of music in online learning, reflection, educational leadership

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The rise in popularity and growth of online learning has moved it from the “periphery of educational delivery to the center of higher education” (Bozkurt & Zawacki-Richter, 2021, p. 3). Increased student enrollment in online courses and fully online instruction delivery created the need for instructors who, heretofore familiar with face-to-face formats, developed the basic skills necessary to deliver quality online instruction (Bozkurt & Zawacki-Richter, 2021; Donelan, et al., 2025; Neuwirth, et al., 2020; Young & Duncan, 2014). The demand for online instruction has assumed the form of blended, asynchronous, and synchronous delivery (Duncan et al., 2013), shifting many educators from K-16 to post graduate school from hybrid delivery to exclusive virtual delivery. Whether learning is delivered face-to-face, hybrid, synchronously, or asynchronously, educational delivery has challenged traditional pedagogical tools and required a “rethinking of educational strategies for the twenty-first century” (Crawford, 2017, p. 1).

One of the pedagogical challenges with which higher education professors who teach online, particularly educational leadership professors, most struggle is how to create and incorporate academically challenging, culturally relevant, and engaging educational experiences using assignments that not only address leadership standards, but that also address the flexibility needs of professional students in a virtual environment (Donelan et al, 2025; Duncan et al., 2013; Neuwirth, et al., 2020). This is especially true in an online environment where in addition to providing practical assignments, professors must also first create authentic community—a community of students who discuss educational challenges, questions, and ideas in real time . Hence, a need and a challenge also exist to create authentic pedagogical strategies. As this study suggests, music is one way to teach online, but little is known about its use in educational leadership practices. Herein, I offer a response to this challenge using music as a pedagogical tool to facilitate the development of the “social and learning communities and foster a shared consensus...” (Rovai, 2002, p. 364).

Purpose and Significance

The purpose of this article is to describe how using music as an introductory educational leadership assignment entitled “Leadership in Song” (LIS) in an online platform successfully creates a cognitive collaborative community of inquiry, specifically around leadership characteristics that fosters a) reflection, b) collaboration, c) recognition of the value of diversity and d) provides a transferrable activity that school leaders can modify for use with various stakeholders in their schools (Miller-Young & Yeo, 2015).

Inasmuch as learning and leadership are fundamentally social in nature, this original assignment, LIS, is significant because it underscores how music as a medium is used to create a collaborative, engaging, relevant, and interactive virtual experience for educational leadership students (Pope & Patterson, 2019). This assignment further emphasizes that learning is social and embodies both a rational and cognitive process (Immordino-Yang & Damasio 2007).

Research Questions

The overarching research question about whether and how music can be leveraged in an online environment is guided by the following questions:

- 1) Whether and how music affects community building in an online environment?
- 2) Whether and how music advances leadership collaboration skills in an online environment?

Theoretical Lens

Grounded in tenets of Active Collaborative Learning (ACL), this assignment centers student-learner experiences by using music as a pedagogical tool to help students find patterns in their lived leadership experiences, organize their patterns into meaningful ideas, and apply their ideas around a singular group experience (Yoder & Hochevar, 2005). Molinillo et al. (2018) contend that “active learning involves speaking, listening, writing, reading, and thinking” (Yoder & Hochevar, 2005) (np). Moreover, using ACL changes the way students learn by moving from a passive role to one that actively manages and develops their learning (Donelan, et al., 2025; Molinillo et al., (2018). Instead of learning passively through LIS, students demonstrate their own agency by becoming architects of new learning and experiences.

Further, LIS leverages a learning modality, music, that has not been a dominant motif in academia or typically used in higher education classrooms to illustrate how music can instill educational leadership concepts (Duncan & Young, 2009; Watson, Bishop, Ferdinand-James, 2017). Equally important in this assignment, music was used as a tool to reinforce leadership skills.

While the use of music is not common in higher education, teachers in the early grades routinely use music as a teaching tool (Foran, 2009). As instruction moves to higher levels of education, strategies as simple as the use of music are considered too elementary. Nevertheless, as Foran argues, when used appropriately, music can evoke positive experiences that “can strengthen healthy neural connections and promote cognitive and emotional development” (p. 54). Further, Foran, Immordino-Yang and Damasio (2007) and Sjolie, Espenes, and Buo, (2022) argue that emotional processes are necessary for transfer of skills and knowledge into long-term memory and real-life situations. Because “modern biology reveals that humans are fundamentally emotional and social creatures” (Immordino-Yang, & Damasio, 2007, p. 3), in this case, connecting judicious use of music to a specific leadership assignment has the potential to promote student engagement through cognitive and emotional connections to ideas (Doolittle et al., 2023; Foran, 2009). When used as an integral part of an introductory lesson in educational leadership, music can potentially promote higher level thinking and better decision-making skills, and lead learners to connections that foster a deeper understanding of the concepts regardless of the level of educational engagement (Immordino-Yang & Damasio, 2007; Jing, 2024).

Lastly, while the assignment's primary task engages the cognitive dimension, by employing an ACL lens, the activities involve social-emotional interaction evoked using music (Sjolie, Espenes, & Buo, 2022, p. 2). As a result, social interaction through music provides the foundation on which the assignment rests.

Methodology

Leadership in Song: The Assignment

"Leadership in Song" (LIS), is an introductory assignment in an elective urban leadership concentration offered in an online Master of Education (M.Ed.) and Educational Doctorate (Ed.D.) program. As an introductory activity for school leaders and teachers, I used music as an emotional connector to build a shared philosophy of leadership. This assignment is designed to a) offer an initial way to create community among a group of students who have no previous relationship with one another, b) foster consensus building and synthesis, c) shift the balance of power from the teacher as the focal point of learning to the student. The following outlines how the assignment was structured within an urban leadership classroom.

Participants

Twenty-one participants in this study were Master of Education and Educational Doctorate students in an elective urban leadership class taught every fall and spring. Participants in this class served as teachers, school and district level leaders, and one person in the judicial system within public-school settings as depicted in Table 1 below. For anonymity, students were assigned a pseudonym beginning with Student A through Student T.

Table 1

School Assignments of Students in Urban Leadership Class

School Assignments	Program	Number of Participants
Classroom Teacher	M. Ed.	9
Building Assistant Principal	Ed.D.	4
Building Principal	Ed.D.	4
District Personnel	M.Ed.	1
District Personnel	Ed.D.	2
Other (juvenile system)	Ed.D.	1
Total	M.Ed. Students	10
	Ed. D. Students	11
		21 Students

Introducing the Assignment

To introduce the assignment, model the use of music as a teaching strategy, and establish a commonality of purpose, the professor used a song that resonated with the professor's philosophy of leadership. In this study, "I Am Light" by India Arie was used. The song was introduced by telling students that "I am playing a song that represents my philosophy of educational leadership." After playing the song, I explained how my philosophy of educational leadership relates to the song's lyrics.

Next, students organized themselves into groups that last throughout three semesters, entailing three urban leadership courses. Because this course is the first of three urban educational leadership courses, this exercise is the first step in creating purposeful communities of learners.

Crafting Philosophies of Leadership and Choosing Their Songs

Over the next week, students wrote their individual philosophies of school leadership, then shared and discussed their philosophies with their groups. Through consensus and synthesis, each group developed a “group” philosophy of school leadership. After synthesizing their individual philosophies and developing their group philosophy of school leadership, students collectively selected a song that embodies their composite philosophy of leadership. Using their class readings to contextualize and support their explanations of “leadership in song,” students crafted a group explanation of how the lyrics in their songs relate to their collective philosophies of educational leadership. As a result, the overall experience allowed students to conceptualize a significant component of leadership: a definition of who the person and the group are as leaders.

As a final step, students answered the following four questions:

- 1) What is the value or relevance of the assignment?
- 2) What did you learn from the assignment?
- 3) How could the assignment be used in other settings?
- 4) How or in what way(s) would you modify the assignment?

Students answered these questions individually.

Data Collection

After completing the assignment, students submitted the following: 1) individual philosophies of educational leadership 2) collective philosophies of educational leadership, 3) group song with an explanation of the connections between their philosophy and the song’s lyrics, 4) and individual responses to four questions describing the value of the assignment, what they learned, how they might use the assignment in other settings, and any possible modifications. Groups then submitted all explanations and responses in Power Point, Prezzi, or Word Doc format along with either a video or the lyrics of the song in our digital learning management system, Desire2Learn. For this article, findings are reported from individual responses to questions one and two on the relevance of the assignment and what they learned. A forthcoming paper discusses students’ responses to the way in which the assignment relates to their group songs and their philosophies of leadership.

Data Analysis

Using the tools of analysis as outlined by Saldana (2016) and informed by tenets of Action Research related to collaborative action research (Efron & Ravid, 2016), I analyzed the data by using open and axial coding, noting patterns, and maintaining a chain of evidence (Merriam, 2002; Saldana, 2016). Based on student responses to the action research questions, this analysis included several iterative steps::

- 1) Compilation of group responses from the four questions entitled “Leadership in Song composite responses,

- 2) Compilation of codes from the composite responses entitled Coded – Leadership in Song – composite responses,
- 3) Compilation of themes by the guiding research questions, and finally,
- 4) A compilation of responses by individual students.

In this way, I created a chain of evidence for the responses that could easily be traced by each individual student. Below is a more detailed explanation of the content analysis process.

First, I compiled each group's responses to the four questions organized by question with individual responses under each question in a document entitled "Leadership in Song Composite Responses." After compiling the four questions per group into one document, I reviewed the responses several times and open coded the responses to all four questions. While coding, I also made notes of initial themes in track changes. I called this document "Coded-Leadership in Song—Composite Responses" in which I collapsed the codes by question and individuals into themes. After identifying themes of individuals, I combined similar themes with individual names and comments across questions and groups. For example, for question 1 (What is the value of this assignment?) I grouped the various codes into themes such as reflection and collaboration. I recorded the themes along with the individual person on a document entitled "Summary of Themes" for the question. In this way, I identified individual themes as well as individual students who contributed the themes in one document. To explore ways in which music can be leveraged in an online environment, I share students' responses to the two reflective questions: a) What was the value or relevance of the assignment? and b) What did you learn from the assignment?

Results

Student Feedback and Outcomes

In total, 21 M.Ed. and Ed.D. students took urban school leadership as an elective in 2022. Table 2 summarizes recurring themes from students' responses to the value and relevance of the assignment, along with what they learned from the Leadership in Song experience.

Table 2

Themes from Student Responses

Question 1: What did you value or find relevant about the assignment?	Question 2: What did you learn from the assignment?
Reflection about leadership	Reflection about self
Collaboration	Collaboration

Learning effective and ineffective leadership practices	Diversity of leadership practices and perspectives
Affective connections	Opposition

Responses for questions one and two elicited overlapping and nuanced themes in four categories: reflection, collaboration, leadership practices and affective responses. Because of this overlap, I reported what was valued and learned under each theme.

Reflection: What Was Valued and Learned

Reflection was a major theme in response to both the value of the assignment (Question 1) and what students learned (Question 2). Though mentioned more frequently in students' responses to what they learned, reflection was cited as a response to both questions. Students discussed how reflection was valuable to them and described types of reflection. Analysis of student responses revealed aspects of reflection and self-reflection in that students developed an awareness of their personal leadership styles and philosophies, recognized leadership as an evolutionary process, and understood self-reflection as a tool to determine areas for growth and effectiveness.

Self-Reflection

Students valued and learned from the process of reflection. Students saw value in their ability to "dissect personal leadership philosophy, reflect on who they are and empower them to change and facilitate an awareness of the evolution process in leadership" (Student N). Part of this change involved looking "inward to determine the qualities great leaders possess and why these qualities are important" (Student S). A seasoned educator, Student R, admitted that the exercise "made me reflect on my philosophy of education as a new teacher and revisit my philosophy of leadership as a school leader." Similarly, Student N learned that "reflecting on my leadership style was eye-opening. Essentially, this assignment made me think 'Who am I?'" Student Q commented that "I learned a lot about myself in this assignment....I learned how I want to approach leadership in a way that corresponds with my philosophy of leadership."

Introspection

Unlike self-reflection, students valued introspection because it involved not just thinking about leadership in general but thinking about one's individual qualities. For example, Student S, an assistant principal, suggested that "this assignment is an exercise in introspection and forces the student to look inward to determine the qualities great leaders possess and why these qualities are important." Student I offered that "it was important that I deeply consider what I value most in leaders and see if those qualities actually align with whom I am authentically." He continued that "it also challenged me to think about the attributes that I want to demonstrate as I transition into high school administration. This type of assignment is valuable because self-awareness leads to growth and progress."

Collaboration: What Was Valued and Learned

Collaboration was cited in both what students valued and learned. Through collaboration, students learned and valued the opportunities to work as a team to complete an assignment and

appreciated the opportunities for discussion. Among other lessons, students valued opportunities to share core leadership values and learned how and why to build consensus.

Collaborating as a Team to Complete an Assignment

Working as a team allowed students to rely on team members' strengths, share ideas about leadership styles, and engage in rich dialogue. The value of working as a team was important for several students. For example, Student P offered that "by working together as a group we were able to play to one another's strengths to complete the task." It also allows the "opportunity for different individuals to synthesize their philosophies of leadership into one philosophy... to complete a task" (Student J). For example, Student L suggested that there was value in "the opportunity to share ideals and show the connectedness [similarities] with each of our different leadership styles."

Allowed for Discussion

Students cited having the space to engage in discussion as another important theme. They commented that discussion allowed students "to view leadership from a different lens," (Student C). It also afforded students "the ability to discuss qualities of leadership or to discuss the similarities." Student L commented that the collaboration provided the "opportunity to expand ideas of leadership."

Other Lessons Learned

Students felt the assignment helped to determine core leadership values and provided insight into the collaboration process. For example, Student H stated that "we were able to share what is important to us and what we in turn find important to our work." Another student offered that "this assignment provides insight on how we collaborate within our teams and why" (Student O). Specifically, the assignment provided a model for how to build consensus from different perspectives. For example, Student I commented that "through the consensus of each individual philosophy of leadership that it is essential to be inclusive and consider the ideas and opinions of roles. Student I also suggested that this assignment would be a great simulation. Another student offered that "this assignment provides insight on how we collaborate within our teams and why" (Student O).

Leadership Practices

Another theme mentioned by students in both questions was leadership practices. When students discussed what they valued, they mentioned the value in learning about different leadership practices including effective and ineffective leadership practices through self-reflection. When students discussed what they learned about leadership they discussed the diversity and evolution of leadership practices and perspectives. Student N commented that "As leaders in education, we must continually evolve in this ever-changing field. The only way to do that is to reflect on who we are."

Learning Different Leadership Practices

Several participants shared their thoughts about leadership practices. Student J stated, "I learned that individuals have a wide array of ways in which they view leadership." He continued, "recognizing how people perceive leadership will shed light as to why they respond to issues that arise within an organization..." Student C also suggested that part of the diversity of opinions in

leadership is derived “based on an individual’s experiences, surroundings, and personal circumstances.” Student A confirmed that “leadership can come in the form of many ways.” Several students commented that they learned “different leadership styles” and that the assignment brought “people of different ideas together” (Student F). Other students commented that they learned that leadership is a thought process that evolves. For example, Student C offered the process of evolution when she added, “leaders must adjust and evolve based on the needs of their staff, students and various other stakeholder.” Another student commented that “I have learned that there is so much more that goes into the leadership role than what I previously thought” (Student L).

Learning Effective and Ineffective Leadership Practices

Students saw the value in identifying effective and ineffective leadership practices. For example, Student M shared that through this assignment, she could determine “whether my style of leadership is/has been proven effective in my current and previous roles” (Student I). When asked about the value of the assignment, students commented that it afforded them an opportunity to reflect on their individual leadership styles, practices, and beliefs as leaders and classroom teachers. Second, the assignment provided students with a lens to consider the necessity of change by exposing students to other leadership styles, and to consider areas to improve their different schools.

Student I surmised that “leaders should be supportive and build positive relationships.” Student B added that despite their backgrounds and experiences, “good leaders are able to LISTen to others’ perspectives and opinions in order to evolve their approach and thought process.” One of the most insightful comments about what they learned centered around the acknowledgement of differences in intersectionality of ideals. Student H stated that

while we have differences, there are so many areas where we intersect in our ideals... From each of our experiences we were able to share what is important to us and what we in turn find important to our work.

Affective Connections

Students reported four important affective connections to the assignment: affective responses, leveraging music to connect to students, opposition to the assignment, and tension with use of music. Affective responses and leveraging music to connect were distinct responses to question 1, and opposition to the assignment and tension using music were revealed in responses to Question 2. Students suggested that music fosters an affective connection. Student K reported that “selecting a song that we believe embodies our role as educational leaders portrays how heartfelt this profession is. Music comes from the heart and so does working in education, especially in leadership.” Another student commented that it connected her to her youth:

In considering the value or relevance of this type of assignment, I venture to take a mental trip back to my younger years—even before I knew my career path. Briefly reflecting on my young self, I retreated to the quiet stance and opted to simply observe my surroundings and conjure ways to make changes that I considered was need. I still have those similar envisaged moments whenever I see a situation as

problematic or something I would like to be able to improve. Only now, have I made a connection to my feelings about change in my younger years that I have today. (Student K)

Leveraging Music to Connect to Students

Considering the power of music, another student found value in connecting the music to how young people learn and navigate their world: “The relevance of this assignment is that our students seem to learn more about how to navigate life through music, and this assignment made me reflect on how the song resonated with me as a child” (Student T). Through this experience, he was reminded that

our kids are definitely influenced by the culture and you can see that via the novelty tee shirts they wear, and the fact that many of them walk the hall with Air Pods in their ears all day long. They learn through the music, and we educators must leverage that to our advantage. (Student T)

Opposition to the Assignment

Even though most students accepted the assignment, reactions to the assignment ranged from “not passionate about music” (Student P) to challenging with one student who opposed the assignment. She explained that her “default has always been to...work “independently rather than with a group, mainly because I always end up doing all of the work anyway.” Importantly, while this student did not want to do the assignment, she developed some powerful insights about the assignment’s usefulness by its conclusion. In her responses she acknowledged that

my experience with this assignment—really THIS COHORT—is unlike any other that I have experienced. This group pulls their own weight, and everyone is willing to jump in and come to the rescue when one of us is struggling (Student P).

This realization led her to the understanding that “often the power of group work lies in remembering that there is a power in the collective. This is a valuable takeaway—as leaders we must remember that the smartest person in the room is the room.”

For many students using song as the medium was a source of irritation. Some thought the entire assignment off-putting (Student P). Others saw no immediate value (Student K). Still others offered the use of other mediums. The important point is that while they found the assignment difficult because of the different preferences for music, in retrospect, they found value in the assignment after completing it. For example, Student K stated that

INITIAL THOUGHTS [student’s emphasis] I’m just not certain if there was an immediate and beneficial impact based on us joining our philosophies and connecting that verbiage to an agreed upon song. In retrospect, I can see how a musical selection ties into leadership; music and leaders connect to people emotionally, music and leaders have a purpose or message. Music entails instruments and voices which play together or independently – as do the leaders and other contributing staff in the building to move toward a desired outcome.

Student P was equally adamant about the nature of the assignment: “I am not passionate about music: therefore, the nature of this assignment was off-putting to me.” However, after completing the assignment, she added, “I think this the beauty of an assignment takes some of the comfort zone. It forces people to come together to complete a mission ... It taught me the strength of the collective.”

Another student would have preferred to work with students who hold similar positions. This point is particularly important as leaders face more diverse student bodies and parents in their communities. Leadership could be the most challenging aspect of the assignment since teachers must grapple with diversity and address student needs from a culturally responsive perspective. As pointed out in the value of the assignment and how it can be used, participants admitted that this exercise helps leaders learn how to recognize and negotiate not only similarities but also differences and more importantly reach consensus about how to complete a task.

Summary

The personal interaction and tasks imposed by this assignment forced students to collaborate and reflect. The assignment afforded students opportunities to reflect on their own leadership philosophies as well as the leadership philosophies of others. Additionally, students cited to successfully complete the assignment they needed to reflect on who they were as individuals and as leaders. Through this inter- and introspection students learned the diversity of leadership practices, both effective and ineffective.

Discussion

Using ACL as a theoretical lens, the Leadership in Song assignment was designed to use music as a pedagogical tool in an online synchronous educational leadership class to (a) inform practice, (b) build community, and (c) synthesize and construct new ideas around a collective leadership philosophy. More importantly, through orchestrated engagement, these student-learner experiences focused on ACL tenets of speaking, listening, writing, reading, and thinking.

Leadership in Song is an assignment that fosters learning communities connected to a cognitive skill and links an emotional task to a key component of educational leadership, a philosophy of leadership. As such, the findings from this assignment supports a foundation for lasting learning that connects to the emotional as leveraged through music: the song/music connects students to the emotional aspect of the assignment. Students then use that emotional or affective connection to create their individual learning communities. Some students commented that use of the music connected them to their youth and reminded them of the connections contemporary youth make with music.

Pedagogically, music grounds the Leadership in Song assignment and is the focal point from which students engage their “cognitive presence,” defined as the process by which learners construct, confirm, and devise new meaning through “sustained discourse” in a critical community of inquiry (Garrison et al., 2021, p. 1). By using music to address learning styles and

connect the emotional to the cognitive, this exercise contributes to “instructional practice” and the “science of instruction” (Mayer, 2009, p. 1). Using ideas from the class readings, their individual school/leadership experiences, the school/leadership experiences of their peers, this activity allows students to construct their own meanings of leadership through music (Schwon, 1983).

In response to the overarching research question (Whether and how can music be leveraged in an online environment?) the guiding questions included: 1) Whether and how did music affect community building in an online environment? and 2) Whether and how did music advance leadership collaboration skills in an online environment? The central outcomes of this assignment are 1) reflection, 2) the power of collaboration, 3) better understanding of leadership skills, and 4) affective connections.

Reflection

Because active learning and reflection involves speaking, listening, writing, reading, and thinking (Yoder & Hochevar, 2005), reflection was an integral part of the ways in which music advanced leadership collaboration skills. Using music as the focal point of the assignment provided students opportunities for self-reflection about their leadership practices as well as the leadership practices of those in the group. For example, because of group collaborative conversations, the assignment caused students to engage in self-reflection, a necessary skill in leadership. Through the process of looking in the mirror and then listening to peers, students analyzed and accessed their own ideas about leadership in comparison to other ideas. The ensuing introspection coupled with shared ideas fostered a heightened self-awareness that fosters growth and progress.

Collaboration

Assignments such as this provide space for collaboration and introduce prospective leaders to the importance of considering different perspectives, which are essential for effective leadership. Students found value in collaboration citing “the style of assignment allows teamwork and collaboration. It provides each one of us an opportunity to meet and learn about others....” (Student L). Thus, the creation and articulation of a collective philosophy of educational leadership using song allows students to collaboratively reach an educational goal (Garrison, 2007) by: 1) fostering individual and group accountability and group processing around a singular idea, 2) establishing the group’s social presence, 3) building an environment of inquiry and reflective discussion to allow. Further, the collaborative discussions involved in this assignment moved students from a teacher-centered focus on leadership to an active student-centered and student-generated focus on leadership (Sjolie, Espenes, & Buo, 2022).

Collaborative Community

One of the essential elements in online or virtual higher education classrooms has been the necessity of building collaborative communities (Duncan, 2005; Garrison, 2007; Sjolie et al., 2022), especially for working professionals. In contrast to collaboration, building a collaborative community requires sustained collaborative discourse within the same group of people while collaboration may occur occasionally with one goal (Randrup, Druckenmiller & Briggs, 2016). Garrison 2007 argues that “higher education has consistently viewed community as essential to support collaborative learning and discourse associated with higher levels of learning” (p. 61).

Students' collaborative community building skills form the basis of their work for working with their leadership philosophies around the music they select. Naidu (2014) argues that to form the connectivism necessary to build a collaborative community as well as work towards a common goal, "communication, discussion, and debate" (p. 67) are necessary components. Importantly, because the philosophy of leadership in song uniquely belongs to each group, their communities are defined by both their collective philosophies and by their individual songs. In addition to establishing a collaborative online community, this assignment allows for community collaboration outside the online environment through phone conversations, or other communication platforms such as Group Meet, Slack, or Google Doc. The collaboration embedded in this assignment models the type of collaboration that leaders should model and expect from their teachers.

Better Understanding of Leadership Skills

In the process of collaborating and reaching consensus, students found value in learning effective and ineffective leadership practices. As noted, because the class was composed of M.Ed. and Ed.D. students, they found themselves at multiple places on the leadership spectrum. Hence, part of the collaboration consisted in hearing, sharing, and learning from colleagues' diverse leadership experiences including effective and ineffective leadership practices. In part, this exercise functioned as its own professional learning opportunity with the less experienced leaders learning from the more experienced leaders and the seasoned leaders gleaning fresh ideas from the less experienced participants.

Affective Connections

Because of the sustained cognitive collaboration embedded in the Leadership in Song process, students recognize that the groups are also formed for social purposes—to help students get to know each other—and to form a community of learners based on a mutual purpose and inquiry that in turn reinforces their social skills (Garrison, 2007). Undergirded by a positive interdependence, students form not just a social presence but a presence that requires "intellectual focus...and purposeful communication" (p. 63). This collective construction of leadership in song encourages discussions around students' cultural norms, language, values, beliefs, knowledge, and practice represented in their schools (Abrahams, 2005). Experiencing an assignment that promotes social presence and participating in a collaborative community equips students with tools that they can use as school leaders. They learn the power of building and engaging in social activities that move toward purposeful collaborative engagement around a specific purpose. Most important, this assignment models how to engage in and engage others in a collaborative community.

Benefits of Discomfort

Notwithstanding the social purposes of this assignment, affectively, several students commented that they were not passionate about music, and the nature of the assignment was "off-putting." Acknowledging that this type of assignment caused some students discomfort is important. Even though the assignment took students out of their comfort zones, it encouraged them to rely on their team mates to help them make sense of and execute the assignment. Awareness of the possibility that some students may be uncomfortable with the assignment is important because it demonstrated for school leaders who are accustomed to being the person

with the answers, that even leaders need a team to “complete a mission.” This acknowledgement is important because it reinforces the need for teamwork on all levels.

Lessons from the Field

LIS lessons from the field include how I would modify the assignment to meet the needs of others both inside and outside an online learning environment as well as implications for practice.

Modifications for Practice

Given the pedagogical focus of the assignment, I considered modifications for subsequent classes. As a first step for the assignment, I would afford students an opportunity to draft their personal philosophies of leadership. Drafting their own philosophies of leadership would provide them with a basis for combining and drafting a collective philosophy of leadership. As a final step, I would afford students an opportunity to revise their individual philosophies of leadership based on what they learned during the process. Revision as the last step in the assignment is important because it invites students to further explore and broaden their perspectives, re-evaluate, and revise their collective philosophies of leadership. Students then have an opportunity to submit their revised versions of leadership philosophies with an additional explanation of what they changed and a rationale for their changes. Lastly, I would ask students to represent their songs/philosophies in a collage, wordle, or some other visual format, again reinforcing engagement and creativity.

Using music for this assignment worked because each group was charged with finding a song despite diverse music preferences, thus prompted students out of their comfort zones to engage in a task. While some students suggested using other mediums such as a visual art or a movie in lieu of music, I think using music worked best because even though students may not like the same type of music, use of music required students to interact with diverse musical preferences and then reach consensus about the best song to represent their collective ideas. Further, it allowed students to touch the emotional reservoirs of “teaching, research, service and leadership” (Dillard, 2006, p. xii). In this sense, students were expected to respond not only to emotionality that a song inspired, but they had to relate the lyrics directly to their collective philosophies. The cognitive and emotional connection between musicality, the words of a song, and the philosophy of leadership would be lost with the use of other forms of media.

Implications for Practice

While designed for an online class, LIS is appropriate for hybrid or face-to-face classes and can be adapted as a back-to-school opening activity, a community-building exercise, and a motivational exercise. For example, school leaders can use this assignment as an initial back-to-school activity to help faculty coalesce around an idea or identity or to express their feelings about returning to school. The latter might be informative given the anxiety that teachers face around returning to school and teaching post-pandemic or other social or work-related stressors. Additionally, Leadership in Song can easily be modified to include a school-wide philosophy or mission statement, or it can be used to build collaboration among faculty.

Because Leadership in Song is a malleable assignment, it can be used as an excellent professional development tool, team building, and motivational activity to help teachers develop their own philosophies of teaching and learning. It can also be used by teacher leaders and teachers of the same subject to find a song that expresses how they feel about their specific subjects or teaching their classes. Furthermore, students suggested that LIS could be used in K-12 classrooms to build community.

Conclusion

The Leadership in Song assignment is a tool that can be used by school leadership instructors in both online and face-to-face environments to fulfil students' need for social presence, cognitive discourse, and community building by “balancing socio-emotional interaction, building group cohesion and facilitating and modeling respectful critical discourse which is essential “for productive inquiry” (Garrison, 2007, p. 69). It is an example of how an atypical medium, music, can be used to enhance instruction in a graduate level educational leadership class. Even though Garrison (2007) suggests that additional work is needed to ensure that course content and social interactions occur in online teaching, this assignment provides alignment of the course content by affording students the opportunity to define leadership through collaboration. The assignment also offers an opportunity for instructors to engage students in and out of the online classroom environment. Because both successful virtual and face-to-face teaching should provide engagement, relevance, and collaboration, this exercise offers an exemplar of how music might be used to enhance instruction in both settings.

It is very important to note that even though Reflection and Collaboration were common to what students valued and learned, for at least two students, the initial assignment was “off putting.” However, one student, a building level principal, whose default was “to do it” herself offered the most insightful epiphany for this assignment:

Often the power of group work lies in remembering that there is power in the collective. Yes! This is a valuable takeaway—as leaders we must remember that the smartest person in the room is the room. WOW! What a valuable takeaway and reminder that I think leaders often forget. (Student P)

This realization is often missing in educational leadership. Instead of principals, teachers, staff, and district personnel working together to achieve a task, they more often work in siloes.

The crux of the assignment is that no matter how different the ideas, values, and beliefs about leadership, people can come together for a common goal. By extension, one would hope that school leaders, teachers, and district personnel could use the lessons from LIS to inspire collaboration and reflection to build more cohesive and purposeful educational teams.

Declarations

There are no conflicts regarding the publication of this manuscript.

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Promoting and Evaluating Professional Learning Among Teachers Through Open Online Discussions

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Abstract

Discussion is a neglected design element of open online courses but has the potential to promote and evaluate professional learning and knowledge building among working professionals. Professional learning requires application to achieve its aim. Open online courses can reach professionals at scale, but to demonstrate effectiveness, it is important to show that learning can be applied to practice. Existing metrics (e.g. enrollments, tests, quizzes and completions rates) are limited in their capacity to evidence this. However, by designing discussion prompts to elicit professional learning, it is possible to scaffold the application and exchange of knowledge among peers, and thus more effectively track the effectiveness of the course in supporting professionals' learning through social interactions. This paper analyses discussions in an open online course for teachers working in crisis and emergency settings and other challenging environments. By critically synthesizing existing theories, we developed an *Online Discussion Value Framework*, modified it by incorporating preliminary codes derived from qualitative analysis of discussion data (discussion prompts and participating teachers' posts), and, finally, applied it to the full dataset. The findings showed the efficacy of the framework in analyzing the extent to which online discussions were effective to support teachers' quality professional learning. We conclude by elucidating the implications of this study for advancing research into effective online discussions, and for guiding and evaluating discussions as a powerful pedagogical tool to support professional learning in large-scale, open, online courses. Limitations and future research directions are suggested.

Keywords: Online open courses, online discussions, professional learning, teacher professional development scaffolding, social interaction

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Open online courses (e.g. in Massive Open Online Courses or MOOCs) hold great potential for providing affordable teacher professional development (TPD) in contexts where conventional methods are unable to address the scale of the demand. Such circumstances include mass displacement resulting from conflicts and crises that routinely produce teacher shortages. Shortages occur for multiple reasons. For example, teachers within displaced communities may have left or become traumatized and are no longer able to teach (Burns & Lawrie, 2015). School systems within the host community become overwhelmed with the numbers and complex needs of refugee children. In these contexts, TPD provided at scale can make an enormous difference by enabling teachers to become key agents of change for displaced communities and supporting children and young people to prosper both inside and outside the classroom (Pherali, et al., 2020). For these reasons, open online courses are advocated by governments and international organisations such as UNESCO as a viable means for upskilling the teaching profession on a large scale to address equity issues in education (Laurillard & Kennedy, 2017). Professional learning in open online courses is therefore important for equipping teachers with updated professional knowledge to support their students' learning needs, especially those students who come from disadvantaged social backgrounds and regions lacking quality educational resources. Open online courses have also been reported to support professional learning in other fields, such as nursing, health care, social policy (Anderson et al., 2020; Longhini et al., 2021), environmental education (DuBois et al., 2019), engineering, and management (Kop et al., 2011). Studies found that enrolled participants of open online courses were mostly working professionals, in particular educators (Glass et al., 2016; Liu et al., 2020). Professionals like these need applied knowledge gained through collaborative learning (e.g., exchanging experiences and expertise, propose solutions to ill-structured problems) to gain new knowledge and take action in complex workplace situations (Kellogg et al., 2014).

Open online courses offer a range of learning activities, such as viewing educational videos and readings, contributing to online discussions, taking online quizzes, and assessing peer assignments. Such activities assist participants to engage in a technology-supported learning environment and jointly build a community of practice where they socially construct knowledge regardless of their differing geographic locations and cultural backgrounds (Phan, 2018; Rivera et al., 2024; Sullivan et al., 2018). Data traces of participants' engagement with these activities are automatically collected by course platforms and their analysis typically informs course evaluations (Cohen et al., 2019; Kent et al., 2016). Yet none of these activities can effectively track application of learning to practice, which is the objective of such initiatives. This could be achieved, however, through the analysis of contributions to online discussions. To demonstrate the effectiveness of large-scale, open, online courses, therefore, we propose the analysis of discussions to elicit and evaluate professional learning.

Most platforms make online discussions available to participants (Phan, 2018; Quintana et al., 2021). When appropriately designed, online discussions can engage participants in peer learning and collaboration (Galikyan et al., 2021; Kellogg et al., 2014; Koehler et al., 2020), which potentially support participants' achievement of higher-order learning outcomes. Such outcomes range from conceptual understanding and practical applications to the skills of communication, problem-solving, critical thinking, and reflection (Garrison, 2006; Pečar, 2016). Existing research shows that professionals taking open online courses benefit from discussions in several ways. Professionals engaged in online discussions form social networks with peers to

negotiate and co-create professional knowledge which is especially important for those working in isolated locations (DuBois et al., 2019; Quintana et al., 2021), are motivated to apply new learning in their workplace (Anderson et al., 2020), and when appropriately facilitated, can self-reflect and transform pre-existing assumptions (Lee & Brett, 2015).

Nonetheless, the potential of discussions in open online courses to support professional learning outcomes is not always realised. Existing studies found several problems associated with online discussions. Participants' contributions to online discussions were often superficial (Han & Ellis, 2019; Koehler et al., 2020), viewed exclusively as help seeking or giving (Wise & Cui, 2018; Wong et al., 2015), confined largely to social interactions with limited peer collaboration (Cohen et al., 2019; Murphy, 2004), lacked coherence in discussion threads (Kent et al., 2016), and were often performed to merely satisfy course requirements without clarifying personally meaningful goals (Koehler et al., 2020). Furthermore, discussion forums in open online courses are often unstructured, chaotic, and full of irrelevant posts (Wise et al., 2017). Although such problems were reported for participants of open online courses generally, they were especially noticeable for professionals, since professionals typically needed to juggle demands of work, life, and online learning (Liu et al., 2020). To overcome such drawbacks, researchers propose aligning online discussions with expected learning outcomes and providing pedagogical scaffolds such as discussion prompts and moderation to engage participants socially and cognitively (Aloni & Harrington, 2018; Chiu & Hew, 2018; Phan, 2018; Yücel & Usluel, 2016). This paper argues for a similar approach in open online learning for professionals such as schoolteachers working in isolated, challenging contexts in the current study.

The scaffolding of effective online discussions within open online TPD courses for teachers in contexts of mass displacement is a critical step to improving the benefits that such courses can provide. First, it can improve the learning experience for teachers by creating a sense of community for isolated teachers, and enable them to learn from their peers, providing the kind of practical knowledge necessary for challenging environments (Kennedy & Laurillard, 2024). Second, and critically, it can provide evidence of participants' learning, demonstrating the return on investment for funders and providing a potential pathway to professional certification for teachers. With this aim in mind, this paper analyses contributions to online discussions within two iterations of an open online TPD course "Transforming Education in Challenging Environments" (TECE) for teachers working in crises and emergency settings. The course engages participants in discussions and other collaborative activities around video case studies of teachers who are teaching refugees in low-resourced environments. The discussions aim to guide participants to share and build upon the effective practices of peers in a global community of practice and apply the concepts and ideas to their own practice.

Professional Learning in Open Online Discussion

Most existing studies of open online discussion used some form of automated analysis such as keyword search and learning analytics (Wong et al., 2015). Several studies investigated the relationship between the social (e.g., participants' number of posts; social centrality in peer interactions) and cognitive (e.g., quality of participants' posts) aspects of online discussions. Earlier studies reported the relationship between participation in discussions (e.g., number of posts) and course performance (e.g., assessment scores, course completion) (c.f., Palmer et al., 2008). In recent studies employing quantitative methods such as learning analytics and content

analysis, participation in discussions has been associated with course completion, intensity of cognitive activities (e.g., assignment preparation) (Cohen et al., 2019), and learning outcomes (test scores and quality of posts) (Kent et al., 2016). Wise & Cui (2018) found that a small group of strongly socially connected participants were able to discuss substantive content and express learning-related emotions. Galikyan et al., (2021) reported that the social aspect (number of participants' contributions to discussion threads) moderated the relationship between the lowest cognitive engagement (sharing ideas without elaboration or evaluation) and course performance.

As such, existing research largely supports the link between the social and cognitive aspects of discussions but does not discuss specifically whether and how pedagogical scaffolding in discussions facilitate professional learning through social interactions. Neither does the research consider whether participant contributions to discussions could provide evidence that professional learning has taken place. Thus, the primary purpose of this study is to examine these issues qualitatively in the context of the TECE course. Finally, in open online courses, the impact of professional development occurs as professionals put into practice what they have learnt to make changes in the world (Chen et al., 2009; Lee & Brett, 2015; Sullivan et al., 2018). For example, educators need to use their learning to improve the teaching and learning experiences for the children and young people they teach (DuBois et al., 2019). Without this applied learning, the aims of professional development cannot be fully realised. Therefore, this paper considers how social learning in online discussions can contribute to supporting application to practice and evidencing when it has occurred among working professionals. The paper achieves this purpose by exploring the key research question:

To what extent are online discussions effective in supporting participating teachers' professional learning by taking the TECE course?

Studies focusing on the pedagogical design of discussions among professionals in open online courses were often informed by theories stressing the social construction of knowledge. For example, Anderson et al.'s (2020) study of an open online course for healthcare professionals found that those who engaged more actively in social interactions through social media attained higher knowledge outcomes compared with others who had fewer social interactions. These authors framed their study using three theoretical sources. The first was Bandura's social learning theory (Bandura, 1991, 2001), which views learning as a result of learners observing others' behaviour and seeing its consequences; thus learning could not be separated from its social context—this is why many authors referred to “social learning” when discussing the social construction of knowledge during online discussions and other collaborative learning activities (Anderson et al., 2020; Rivera et al., 2024). The second was Lave and Wenger's (1991) situated learning theory, which considers learning to be learners' social construction of knowledge as they collectively solve problems to attain shared goals within their community of practice (e.g., an open online course). The third was connectivism, which suggests that technology-facilitated interactions such as online discussions support cyclical learning by enabling learners to exchange information, share knowledge, and change beliefs, behaviour, and cognition (Goldie, 2016). Connectivism was adopted by Bonafini (2018) as the theoretical lens in a study of online discussions of a TPD open online course, in which the author analysed how super-posters actively built networks that explored and shared information and resources with others. While the aforementioned authors emphasised facilitating

professionals' online discussions as a social process whereby they created, shared, and applied work-related knowledge, Lee and Brett (2015) went further by drawing on Mezirow's (2003) transformative learning theory and Bakhtin's (1981) concept of dialogue to purposefully design and analyse discussions in an online course. Through social interactions during online discussions, teachers represented the self to others, encountered different perspectives which triggered their cognitive dissonance, and engaged in critical self-reflection which helped them transform their pre-existing values and beliefs (Lee & Brett, 2015).

We draw two key points drawn from the above analysis of existing research. First, professional learning in online discussions is essentially a social process that can potentially enhance professional's understanding of course content (e.g., concepts, work-related values, and beliefs) and application of learning to practice by encouraging their sharing of work-related experience and collaborative problem-solving. Second, professional learning in online discussions needs to be supported by instructors' pedagogical scaffolding (i.e., design of discussion prompts and facilitation of interactions), which can enable professionals' social learning within their community of practice. Based on these two points, we propose two sub-research questions for this study:

1. To what extent are instructors' discussion prompts effective in supporting participating teachers' professional learning (understanding of course content and application of learning to practice) in the TECE course?
2. To what extent do teachers' posts exhibit quality professional learning in the course?

Online Discussion Value Framework

To our knowledge, no existing frameworks are available for analysing all elements of online discussions including applied aspects of professional learning. Thus, we have reviewed and critically synthesized three empirically tested theoretical models. These models are relevant to this study, since each of them have been proposed to qualitatively analyse the quality of socially constructed knowledge or understanding and could provide theoretical insights for proposing an analytical framework for this study (see Table 2), which we call Online Discussion Value Framework. The framework allows us to analyse the discussion data of the TECE course to analyse the effectiveness of online discussions in supporting teachers' professional learning. In the framework, we have integrated three theoretical models: (1) Wenger et al.'s (2011) *value creation framework*, (2) Kember et al.'s (2008) *reflective thinking model*, and (3) Murphy's (2004) *peer collaboration model*. We first propose categories for analysing participants' posts. Based on these categories that analyse professional learning, we suggest categories for examining discussion prompts intended to guide professional learning through discussions.

Wenger et al.'s (2011) value creation framework analyses the activities of members of a community of practice in which they share, create, and apply collective knowledge through solving practice-related problems to attain common goals and accumulate collective assets or value for the improvement of practice. Attention to social learning among members of communities of practice makes the model a core conceptual basis for our analytical framework. As this study focuses on professionals' social learning through online discussions, we have taken Wenger et al.'s (2011) concept of value creation which refers to participants' co-construction of

knowledge to transform practice in a community. To create value, participants must engage in iterative cycles of processes whereby they join in activities and exchanges, including:

- (1) sharing experiences (immediate value);
- (2) creating knowledge capital, such as skills, relationships, and resources (potential value);
- (3) applying knowledge capital to practice (applied value);
- (4) improving performance resulting from adapting approaches to effect changes in practice (realised value);
- (5) reconsidering strategies, goals, and success criteria to transform practice, which necessitates critical reflection (reframing value).

In communities of practice such as open online TPD courses, participants can potentially create professional value by engaging in iterative value creation cycles through interacting with peer professionals. Wenger et al.'s (2011) framework informed Booth & Kellogg's (2015) case study of school teachers' stories of knowledge sharing and co-creation through the five iterative cycles when participating in informal online teacher communities. We have adapted the category "sharing experiences" to indicate a lower level of participant understanding, while the adapted categories of "application of theory or personal insights" and "reframing" are used to indicate higher levels of participant understanding. Then we have integrated Kember et al.'s (2008) category critical reflection (see its explanation in next paragraph) with Wenger et al.'s (2011) category of reframing value to indicate participants' re-examination of personal perspectives and professional practices by engaging in critical reflection. Integrating value creation into the analytical framework allows us, therefore, to account for professional learning within the discussion.

Kember et al.'s (2008) reflective thinking model distinguishes different qualities of reflective thinking demonstrated by learners' online discussions or written work. The model comprises four categories: (1) habitual action (following a procedure or routine without thinking about the underlying concept); (2) understanding (attempts to find the underlying meaning of a concept or theory without realising its relevance to personal experience or real-life problems); (3) reflection (considering a concept in relation to personal experience or its application in practice, often showing personal insights); (4) critical reflection (re-examining deep-rooted beliefs to transform existing perspectives or practice). The model informed a number of empirical studies that analysed learners' online discussions (Radović et al., 2023) or written work (e.g., Liu et al., 2022). For example, the model informed Radović et al.'s (2023) analysis of open university students' online discussions, which concluded that the discussions contributed to students' deeper understanding and higher levels of reflection, and was associated with learning motivation and satisfaction. From Kember et al.'s (2008) model, we have borrowed reflection as an intermediate category describing participants' reflection on personal experiences, real-life situations, or professional practices without challenging personal (or others') perspectives.

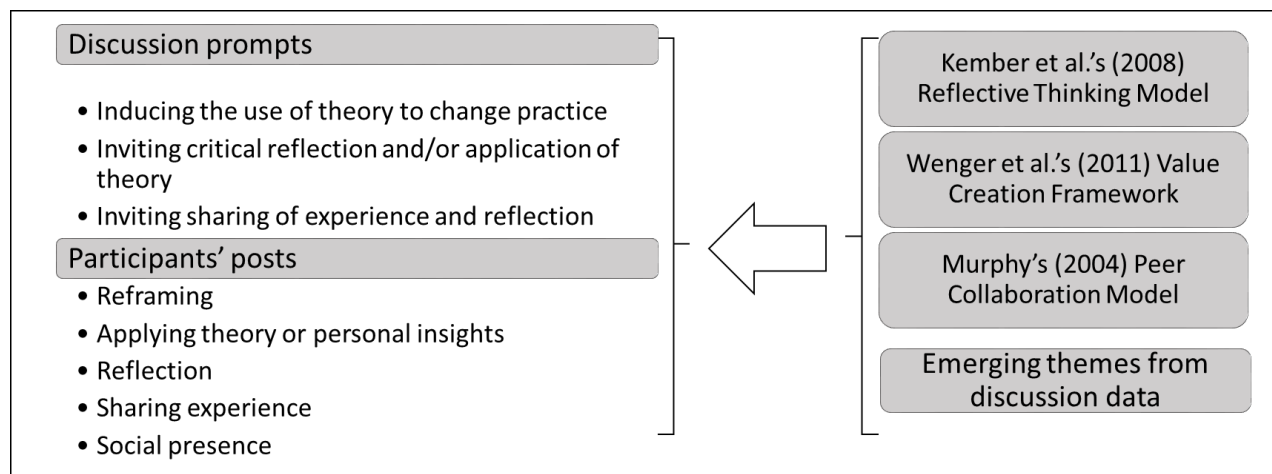
Murphy's (2004) peer collaboration model pertains to collaborative peer learning processes in online discussions, which proceed from simple to complex peer interactions. These include: (1) social presence (e.g., exchanging personal information, showing appreciation); (2) sharing personal perspectives; (3) accommodating and reflecting on peers' perspectives; (4)

constructing shared perspectives; (5) negotiating shared goals; (6) producing shared artifacts. Schaefer et al. (2019) adapted the model to analyse the role of social presence and instructor facilitation during online discussions in an online course, and reported both factors being important for participants' collaborative learning. We have adapted the category of "social presence" (the basic level) to describe participants' posts (or elicitation of such posts by discussion prompts) that only serve a social purpose.

The preceding paragraphs have identified and explained how the Online Discussion Value Framework evolved from its theoretical sources, which helps clarify the conceptual background of the framework based on literature review. It is also important to note that the framework is informed by preliminary codes derived from a qualitative analysis of the discussion data of TECE, so that it is grounded in data (see subsection Ensuring Validity in Methodology (Brooks et al., 2015) (see subsection Data analysis in Methodology for details). Identifying these sources help enhance the theoretical/historical validity of the framework (see subsection Validity in this study in Methodology for more details). Figure 1 summarises the sources informing the framework. The description of the categories in the framework is presented in Table 2 of the subsection on Data analysis in Methodology.

Figure 1

Sources That Have Informed the Online Discussion Value Framework



Methodology

Research Approach and Context

To understand the extent to which instructors' pedagogical scaffolding of online discussions (in particular, discussion prompts) supported participating teachers' professional learning in TECE, we employed a qualitative approach to collect and analyse the rich data from online discussions, including instructors' discussion prompts and participating teachers' posts. By exploring the qualitative data, we derived preliminary codes and compared such codes with the categories derived from the theoretical models previously noted. This formed the basis upon which we developed the Online Discussion Value Framework. Thereafter, we tested it against the dataset to refine it, as themes emerged to address the research questions.

TECE was co-designed by researchers from the RELIEF Centre (a collaboration among University College London, Centre for Lebanese Studies, and American University Beirut) with teachers and teacher-educators from public and private universities, NGOs, and government bodies in Lebanon. The course conceived of teachers working in conditions of mass displacement and other challenging contexts as “transformative intellectuals.” Relevant theoretical concepts are introduced to promote teaching that is caring, creative with limited resources, committed to a holistic understanding of the child in context, and capable of challenging dominant thinking. The instructional videos were shot on location in Lebanon, a country with the highest per capita number of refugees in the world, foregrounding the work of teachers (many of whom were themselves refugees).

Data Collection and Participants

The discussion data were drawn from the first two runs of TECE. From both runs of the course, one step (i.e., unit) per week of the four-week course was selected (see Table 1). In run 1, 1203 participants enrolled, 721 took part and 187 participated in discussions. In run 2, 1637 enrolled, 1107 took part and 318 participated in discussions. Permission was gained from participants and course instructors for quoting the discussion prompts and posts. Their names are replaced with gender-neutral pseudonyms to maintain confidentiality. From the selected units, a total of eight discussion prompts and 559 posts were collected for qualitative analysis. The sample of participants comprised those who enrolled in the two runs of the course and participated in online discussions.

Table 1

Selected Steps in TECE

Week	Selected steps
Week 1	Step 1.2: A challenge for educators
Week 2	Step 2.4: Applying the Ecological Systems Theory
Week 3	Step 3.11 in Run 1 (renumbered as 3.10 in Run 2): Limits to what we can do as educators
Week 4	Step 4.10: How can digital tools help?

Data Analysis

Our evaluation of online discussions can be described as a bottom-up template analysis (Brooks et al., 2015). We adopted a contextualist epistemological position that acknowledges there may be multiple interpretations of the qualitative data, but that the results of the analysis are justified on the basis that they are grounded in the data gathered in a naturalistic research setting (Madill et al., 2000).

The two researchers collaboratively used NVivo 12 to code the data, sharing the amalgamated codes and sub-codes, as well as data files to enable each researcher to use and amend the same template. We adopted four stages of data analysis to enhance the face and content validity of the analytical framework and trustworthiness of qualitative findings (see subsection Ensuring Validity in this study).

In Stage 1, preliminary, open codes were developed by immersion in the data. This involved review of online discussions by two independent researchers who made notes about key ideas of the text, summarised the notes into preliminary codes, then collaborated to resolve disagreement through regular research meetings. We first generated the preliminary codes by analysing the online discussions in Run 1. Then we applied the codes to the discussions in Run 2, making refinements to ensure that the preliminary codes captured the key ideas of the discussion data.

In Stage 2, the researchers compared preliminary codes with the categories derived from the three existing theoretical models (see Figure 1 in the section Online Discussion Value Framework). In this process, further themes and subthemes emerged from the remaining data and were incorporated into the framework. For example, a new subtheme, “sharing artefacts” (sharing collective knowledge products as a novel approach to practice), was added to the theme “reframing,” which expanded the original meaning (engaging in critical reflection to reframe beliefs or practice) of the theme.

In Stage 3, the Online Discussion Value Framework was developed as a template to aid the coding of data in order to analyse the extent to which the discussions were effective in supporting professional learning in terms of the quality of professional learning that discussion prompts were intended to elicit from participants and the quality of professional learning as demonstrated by participants’ posts. We then revisited the framework in the light of our preliminary codes which were incorporated to create the final template (Table 2) for analysis. This process continued as the template was used to analyse the full dataset.

Finally, in Stage 4, the resulting template was re-applied to a subsection of the data (discussions in Run 2) to ensure that it remained a good fit.

Table 2*Online Discussion Value Framework*

Themes	Description
Template for analysing discussion prompts	
Encouraging the use of theory to change practice	Prompting theory informed practice – the adaptation of theory to one’s own context to transform existing practice
Inviting critical reflection and application of theory	Inviting critical reflection and / or application of theory, but not necessarily changing existing practice
Inviting sharing of experience and reflection	Inviting experience sharing and reflection, without necessarily engaging in critical analysis of problems in one’s context
Template for analysing discussion posts	
Reframing	Posts showing engagement in critical reflection or sharing of collective knowledge products to transform (i.e., rethink and reshape) one’s beliefs or transform practice
Applying theory or personal insights	Posts demonstrating realised value or applied value where personal insights/ideas are used to improve practice
Reflection	Posts showing reflection on experiences, situations, and/or practices
Sharing experience	Posts that share experiences, situations, and/or practices without reflection
Social presence	Posts that primarily serve social purposes; sometimes expressing a vague / irrelevant idea

Ensuring Validity in this Study

Validity and credibility of this qualitative study were guaranteed using several strategies. First, we used an iterative process of data analysis, including regular meetings between the researchers to check consistency in analysis and testing of the rationale for addition of new themes or subthemes. Such a process ensured the theoretical validity (the extent to which the relationships between the codes/subcodes are applicable to similar contexts) and face/content validity (the extent to which the categories or codes/subcodes accurately reflected a full range of meaning made by research participants) of the analytical framework (Gaber & Gaber, 2010), and as the trustworthiness of qualitative findings (the extent to which findings were grounded in the data) (Madill et al., 2000).

Second, validity was increased by using peer review (Creswell & Miller, 2000). The researchers invited an external reviewer who was familiar with TECE to offer critical comments. This resulted in refinements to the analytical framework and interpretation of emerging themes. One example was adding social presence from Murphy (2004) for analysing participants’ posts and modifying the interpretation of discussion posts in this category (instead of merely serving social purposes, such posts helped to create a warm social environment for teachers’ professional learning).

Third, to enhance the applicability of the analytical framework and findings to similar contexts (e.g., other open online courses for professional development), we have presented a

thick description of the research context and process, as well as illustration of the themes with rich quotes. These strategies help readers determine whether the research outcomes of this study are transferable to their own contexts (Miles & Huberman, 1994).

Fourth, validity was ensured by additional means, including research notes on major decisions (e.g., selection of online discussions) and prolonged engagement in the research context (e.g., ongoing observations of online discussions of TECE) to ensure that the findings of this study are dependable (Creswell & Miller, 2000).

Findings and Discussion

Findings from analysis of the eight online discussions in TECE are considered below. The analysis identifies and interprets the effectiveness of the framing of discussion prompts in supporting the quality of learning as expressed by teachers' discussion posts in response to the prompts. We present the themes related to these elements of online discussions by providing illustrative quotes, discussing the themes in relation to research literature and elaborating on their implications for practitioners of open online and blended learning courses.

Discussion Prompts

In TECE, discussion prompts were offered at the end of each unit in the course, following each item of video or text, and accompanying exercises. They were deliberately designed to create meaningful discussion, rather than encourage superficial posts found in previous research (c.f., Han & Ellis, 2019; Wise & Cui, 2018).

As displayed in Table 3, the discussion prompts were coded into three categories, including: (a) encouraging the use of theory to change practice, (b) inviting critical reflection, and (c) inviting experience sharing and reflection. Table 3 shows these themes and the text of the prompts. The levels of participants' understanding intended by these three categories of prompts formed a hierarchical structure, like Kember et al.'s (2008) and Murphy's (2004) models for analysing online discussions or written assignments, as well as Wenger et al.'s (2011) model for examining collective knowledge construction in communities of practice. Our analysis found that there was a connection between the complexity of the responses and the design of the prompts (see subsection "Participants' Posts"). This echoes other authors' (Koehler et al., 2020; Pečar, 2016; Phan, 2018) suggestion that discussion posts should be purposefully designed to provide pedagogical scaffolding for professional learning in discussions of open online courses.

Four prompts were coded as "theory informed practice," which elicited participants' understanding at the highest level of complexity by asking participants to demonstrate critical reflection or apply theory with a view to changing their existing beliefs or practice. One prompt was categorised as "inviting critical reflection," eliciting participants' understanding at an intermediate level of complexity by inviting their examination or evaluation of an experience or a situation but not necessarily aiming to change practice. Together, these prompts aimed to promote participants' learning at the levels of "reframing" and "applying theory or personal insights" (see subsection Participants' Posts). These prompts aimed to stimulate participants' complex understanding (Kember et al., 2008) or higher levels cognitive engagement (Galikyan et al., 2021).

Three discussion prompts were coded as inviting experience, sharing, and reflection. These prompts elicited participants' basic understanding at a lower cognitive level (Galikyan et al., 2021; Kember et al., 2008) "reflection" or "sharing experience". Despite such limitations, these prompts supported participants' sense of being members of a community of practice by encouraging their active involvement in discussions and enabling their professional learning through social interactions with peers (Schaefer et al., 2019).

Although the prompt for Step 4.10 in Run 2 was an adaptation of the prompt in Run 1, it unwittingly elicited a lower level of understanding. While the prompt of Step 4.10 in Run 1 asked participants to demonstrate complex understanding (encouraging the use of theory to change practice), in Run 2 the prompt for the same step asked participants to show basic understanding (inviting sharing of experience and reflection). This finding implies that instructors need to think carefully about (re)designing prompts at appropriate cognitive levels to optimise participants' learning and to critically evaluate discussion questions and facilitation before/during discussions, so that social learning is guided towards higher levels of understanding and knowledge application (Anderson et al., 2020; Lee & Brett, 2015).

Discussion Posts

Teachers' posts extracted from the eight online discussions were coded into five themes: reframing, applying theory or personal insights, reflection, sharing experience, and social presence, which we analyse in detail below.

Reframing

Reframing captures participants' engagement in critical reflection or sharing of collective knowledge products to transform beliefs or practice, where the sharing of ideas or products is accompanied by evaluation or examination. Since reframing represents the highest level of complexity in participants' understanding and places a high demand of participants' cognitive thinking (Galikyan et al., 2021; Kember et al., 2008), it is not surprising that just 48 (8.6%) of the 559 posts were coded into this theme.

The following quote illustrates a participant's critical reflection on how teachers' practice in a challenging situation could be transformed by applying Bronfenbrenner's (2000) ecological systems theory to elevate children from financial difficulties affecting their education. The post responded to the prompt of Step 2.4 in Run 2 asking for "one line each to describe the situation, what they did, which of the ecological systems they worked in, and what they could have done further."

Two children from a family were unable to attend school due to the cost of book and uniform fees. I discussed the issue with the guidance teacher and addressed the issue with the social worker to fill paperwork for providing funds for the children. I was working within the mesosystem while addressing the issue with the guidance teacher and within the exosystem when addressing it with the social worker. We could have gone to the School Head as it happens with many students; we could have worked with the village chief to create a committee to raise the funds... These changes are in the exosystem. (Indigo, participant, Step 2.4, Run 2)

In this post, the application of terms “mesosystem” and “exosystem” to the teachers’ practice demonstrated Indigo’s understanding of the way such practice could influence not just students’ school experience, but also the other social systems in which the students inhabited. Indigo went further to show how, on reflection, teachers could have reframed practice by working with the students’ community.

Some participants shared knowledge products with a view to changing practice, as illustrated by Teri’s post that responded to the prompt of Step 4.10 in Run 1 (see Table 3) asking participants to critique and redesign an existing learning design. Terri shared the redesign and explained how the adjustments suited learners’ preferences.

There is a real-life aspect to the design that is lacking.... Where I am in Africa, it is a down-to-earth society from the get-go and (people) would like to experience things before diving into technical aspects and theory.... A section for [digital artefacts] have been added as a means to share learners’ real-life input, in addition to that of the instructor. [link to learning design] (Teri, participant, Step 4.10, Run 1)

It could be seen that the posts in the category of “reframing” demonstrated participants’ critical reflection or sharing of knowledge outputs with an intention to reshape beliefs (Kember et al., 2008) or transform practice (Wenger et al., 2011). Such posts indicated participants’ reframing value in Wenger et al.’s (2011) value creation model. The scarcity of posts coded into this theme suggests that most professionals need instructors’ facilitation during discussions to attain a high level of critical reflection which helps transform their perspectives through meaningful peer interactions (Lee & Brett, 2015).

Applying Theory or Personal Insights

The theme “applying theory or personal insights” demonstrated participants’ application of a newly learned theory or a new personal insight to improve practice, which necessitated critical reflection or in-depth evaluation. Thus, this theme indicates an intermediate level of complexity in participants’ understanding. Of the 559 posts, 144 (25.8%) were classified in this category.

The post below shows a participant’s application of theory in response to the prompt of Step 3.10 in Run 1 asking participants to discuss barriers to applying transformative teaching approaches and suggest solutions:

If you have parents who are unwilling to take an interest in the child's education or principals who see their role as just mainly running the school.... then these create a barrier to the process of Transformative Education. To overcome these barriers, you could build relationships with other teachers and share ideas and concerns with them. Then usually those teachers will collaboratively join to help. Once the principal and parents see positive changes in the child, they will eventually want to help too.... (Blue, participant, Step 3.10, Run 1)

In the post, Blue applied a transformative approach (building positive relationships) learned in the course by analysing a situation where the stakeholders were uninterested in children’s education and suggesting ways to build positive relationships with them. Blue could

go further by addressing the roots underlying the stakeholders' reluctance to improve children's education to thoroughly resolve the barrier.

In another post, Ryan applied ecological systems theory by interpreting a challenging situation in terms of the teacher thinking beyond their micro context to the wider macro context that the children also inhabit, which showed her understanding of the rationale for applying the theory in real-life situations.

I believe teachers need to be prepared to discuss these macro issues (discrimination, harassment and segregation of refugees) to help children understand the environment better and cope in a healthy way. (Ryan, participant, Step 2.4, Run 2)

While the above posts demonstrate participants' application of theories to learning situations, the following post by Daryl shows the use of personal insights to critically analyse digital methods, which responded to the prompt of Step 4.10 of Run 2 asking about their ideas about the digital methods they experienced (see Table 3).

Technology can be a double-edged sword. We can all relate to a server breaking down, rendering the Interactive White Board unusable as well as notepads, laptops and other resources. On the flip side, technology has changed teaching considerably, helping to engage children fully in lessons. Children are more enthusiastic at working digitally. (Daryl, participant, Step 4.10, Run 2)

As analysed above, posts in this category demonstrated participants' creation of applied value (applying knowledge to improve practice) (Wenger et al., 2011). Nevertheless, these posts did not show an intention to transform practice, which usually required reshaping beliefs and activities of their local context (Kember et al., 2008; Wenger et al., 2011). Thus, these posts showed less complex understanding (or a lower cognitive level) compared with those in the reframing category. Despite this limitation, such posts showed participants' capability to transfer new learning to practice, which was a valuable learning outcome from their collaborative social learning (Schaefer et al., 2019). Since critical reflection is a complex form of understanding, the finding that a quarter of posts are coded under this theme implies that the online discussions were effective in supporting quality professional learning.

Reflection

Reflection denotes participants' perception of an experience, practice, and/or situations which were lacking in attempts to examine or evaluate such experience or practice or integrate theory into practice. 259 (46.3%) of the 559 posts were classified into this category, which was nearly half of all posts in the eight discussions.

The post below responded to the prompt in Step 1.2 of Run 1 asking participants to share good teaching and learning environments they experienced and explain why they felt so (see Table 3).

When I was a student, I enjoyed a lot and learned a lot from informal activities like playing or when I was tasked to do the activities. Now I am a teacher, my students learn a lot when they do more activities. (Eden, participant, Step 1.2, Run 1)

In this post, Eden shared positive learning and teaching experiences, but did not analyse what made such experiences positive, which did not fully address the prompt.

In a post responding to the prompt of Step 4.10 in Run 2 inviting participants to share thoughts about digital methods learned in the course (see Table 3), Harper shared concerns and potential benefits of digital methods, but did not engage in examination or evaluation of such methods.

I feel a bit intimidated by technology. I am worried that it will go wrong and the lesson will fall apart. However, I can see some benefits of using it and the students would definitely find the lessons more engaging. I have found this online course very useful and enjoy the combination of video, written work and interactive elements. (Harper, participant, Step 4.1, Run 2)

To summarise, posts coded as reflection demonstrated participants' basic understanding, which was at a lower cognitive level compared with reframing and applying theory or personal insights. These posts indicated participants' potential value created through online discussions, that is, the creation of potential personal and collective knowledge capital (Wenger et al., 2011), which had yet to be applied or realised by engaging in critical examination of experiences, situations or by applying theory to practice. Thus, how professionals can be supported to move beyond reflection in online discussions deserves instructors' careful consideration when designing discussion prompts, so that professionals are guided to go beyond superficially sharing ideas without further evaluating such ideas to improve understanding (Booth & Kellogg, 2015; Pečar, 2016).

Sharing Experience

Sharing experience captures the meaning of posts in which participants shared experiences, situations, or practices without engaging in reflection, which is another category representing participants' basic understanding. Nearly a quarter of the 559 posts being analysed (102 posts; 18.2% of all posts) fell into this category.

In the following post responding to the prompt of Step 1.2 of Run 1 asking participants to share and explain good learning environments they experienced (see Table 3), Jean described the elements of positive environments without explaining "What made it good for you?" as instructed.

At primary school, the teacher used to decorate the classroom with our best work. Everyone tried to produce the best work so that it is displayed in the classroom before the end of the school year. The teacher assisted some students, so that everyone had a chance to have at least one work displayed. It was great. (Jean, participant, Step 1.2, Run 1)

Similarly, in the post below (responding to the prompt of Step 4.10 of Run 2) asking participants to share ideas of digital methods learned in the course (see Table 3). Gabriel described a difficult situation where technological resources were lacking in the learning environment, but did not go further to explain the causes for, or the solutions to, the difficulties.

In our country, Lebanon, internet is not that fast. We sometimes face difficulties in using online learning. Some students don't have the necessary tools at home which makes it even more difficult. (Gabriel, participant, Step 4.10, Run 2)

As the above analysis suggests, posts coded as sharing experience facilitated participants' exchange of experiences, situations, or practices, which were indicative of participants' immediate value (sharing of stories or experiences) (Wenger et al., 2011) created through discussions. Such posts did not illuminate ways to improve practice. Thus, the posts in the category sharing experience were at a lower level of cognitive complexity compared with posts in the category reflection. One common feature of many posts in discussion forums of open online courses is participants' superficial sharing of experience without reflection (Schaefer et al., 2019; Wise & Cui, 2018). Though such posts are important in establishing a collaborative learning atmosphere, undoubtedly instructors need to move professionals' social learning beyond such basic understanding to attain higher learning outcomes.

Social Presence

Social presence represents the posts that either served social purposes without concretely answering the questions asked in discussion prompts or expressed ideas that were irrelevant to the prompts. Just 8 (1.4%) of the 559 posts were coded into this category.

In the following posts, Mackenzie and Nico showed an intention to interact with others but did not respond to the prompts (prompt in Step 1.2 of Run 2 - to share and explain personal learning and teaching experiences; prompt in Step 4.10, Run 2 - to express ideas about digital methods learned in the course).

I am happy to join with you on education in a challenging environment. I hope to get many experiences from you. (Mackenzie, participant, Step 1.2, Run 2)

This week will allow further digital implementation—looking forward to it. (Nico, participant, Step 4.10, Run 2)

The post below responded to the prompt for Step 2.4 of Run 2 that invited participants to analyse a difficult situation and suggest actions to improve it by applying a theory (ecological systems theory). In the post, Skylar saw the helpfulness of the theory but did not examine how the theory could help in improving practice.

I feel the concept of the ecological system theory is very interesting and applicable especially in emergency context. This will enhance teaching and learning especially for children and young adults in our community of services. (Skylar, participant, Step 2.4, Run 2)

Based on the above analysis, although the posts coded as social presence showed participants' willingness to communicate socially with others (Murphy, 2004), such posts demonstrated basic understanding (or what Wenger et al. (2011) called "immediate value"). Without expressing ideas related to the substantive content, such posts had limited utility in participants' collaborative knowledge building (Aloni & Harrington, 2018; Wise & Cui, 2018). This is particularly relevant to professionals taking open online courses, who learn better when

they are facilitated to share work-related experiences and solve workplace problems, and to negotiate and create new knowledge, and to apply new knowledge to practice (Radović et al., 2023; Schaefer et al., 2019).

Summary

Most posts in the eight discussions were classified as reframing, applying theory or personal insights, and reflection, representing complex understanding (Kember et al., 2008) or higher levels of cognitive thinking (Galikyan et al., 2021). Such posts implied participants' creation of reframing value, applied value, and potential value through online discussions, which are the more advanced cycles in Wenger et al.'s (2011) value creation Model. A minority of the posts were categorised as sharing experience and social presence, which showed basic understanding or lower levels of cognitive thinking, or served social purposes, suggesting participants' creation of immediate value (Wenger et al., 2011). Despite such limitations, the posts in these two categories were meaningful to the extent that participants sharing such posts were more likely to gain peers' and instructors' social support, which might encourage them to become more cognitively engaged in discussions subsequently (Garrison, 2006; Kellogg et al., 2014; Radović et al., 2023).

The quality of professional learning that the posts demonstrated was largely in line with the kind of understanding that the discussion prompts had been designed to elicit from participant (see Table 3). For example, the discussion prompts of Step 1.2 of Run 1 and Run 2 (coded as “inviting sharing of experience and reflection”) aimed to elicit participants' sharing and explanation of teaching-learning environments they experienced. Following instructions in these two steps, most participants put forward posts to show their application of theory/personal insights, or to share their reflection/experience. On the other hand, the prompts of Step 3.10 in Run 1 and Step 3.11 in Run 2 asked participants to apply theory to their local situation and suggest solutions for overcoming potential barriers, eliciting posts that were mostly coded as reframing, applying theory or personal insights, or reflection, which were at higher cognitive levels compared with those in Step 1.2 of the two Runs. These findings illustrated that when discussion prompts target at professional learning outcomes, professionals can be encouraged and supported to attain such outcomes, which echoes and provide evidence for other authors' (DuBois et al., 2019; Koehler et al., 2020; Phan, 2018) argument that online discussions can become a powerful tool to scaffold meaningful professional learning.

Conclusion

The failure of most open online courses to embed opportunities for social and collaborative learning is considered an “important obstacle that prevents them from reaching their potential” (Cohen et al., 2019, p. 193). Although researchers argued for the role of discussions to promote professionals' social learning in open online courses (c.f., Aloni & Harrington, 2018; Koehler et al., 2020), previous studies seldom examined the effectiveness of discussions (in particular, discussion prompts as a form of pedagogical scaffolding) in tandem with the quality of learning exhibited by professionals' contributions to discussions. This study was conducted to fill this gap.

We have proposed an Online Discussion Value Framework based on a critical synthesis of existing theories (Kember et al., 2008; Murphy, 2004; Wenger et al., 2011), which was refined

by applying it to the qualitative data from online discussions of the course under study. From the qualitative findings, we draw two conclusions. First, most discussion prompts were oriented to inducing participants' complex understanding and application of learning to practice. Second, most participating teachers' discussion posts demonstrated good qualities of professional learning and application of this learning to practice. Hence, we conclude that overall, online discussions in the course were effective in supporting teachers' professional learning. These findings provided evidence supporting other researchers' (e.g., Anderson et al., 2020; Phan, 2018; Rivera et al., 2024) assertion that online discussions, when appropriately designed, can promote professionals' quality learning through social interactions whereby they negotiate, create, share, and apply new work-related knowledge in their open online course as a community of practice. More importantly, the findings went beyond existing research by showing clear connections between instructors' discussion prompts and professionals' contributions both cognitively and socially

Implications

The research outcomes of this study have significant implications for enhancing and evidencing the effectiveness of online discussions in supporting quality professional learning in open online courses, small close online courses and blended-learning courses.

This study has proposed a new analytical framework to qualitatively analyse online discussions, departing from previous studies that mostly employed quantitative analysis (e.g., Chiu & Hew, 2018; Cohen et al., 2019; Kent et al., 2016). Key to this framework is the attention to professionals' social learning. Further studies may test, extend and/or revise it by analysing online discussions in different professional fields (e.g., social work, law, engineering, nursing, and management). Given the size and reach of open online courses, further research would benefit from using the framework as a basis for automating analysis of open online discussions.

This study provides practical implications. First, concurring with theoretical insights regarding learners' reflective thinking (Kember et al., 2008; Pečar, 2016), productive peer collaboration (Murphy, 2004; Schaefer et al., 2019), and collaborative knowledge creation to change professionals' perspectives and practice (Lee & Brett, 2015; Macià & García, 2016; Wenger et al., 2011), the findings showed that discussion prompts should be designed to orient professionals' understanding towards higher-order learning outcomes, such as applying theory to practice and critical reflection for transforming practice. Instructors can use the Online Discussion Value Framework as a guide to purposefully align online discussions to such professional learning outcomes. Second, templates for analysing participants' posts in our framework can inform meaningful evaluations of learning in open online courses either to evidence learning for stakeholders e.g. funders, or for participants themselves. In the latter case, the template could be used as a self-assessment tool to support participants to self-evaluate whether their shared ideas showed more complex (e.g., Applying theory) or basic (e.g., Sharing experience) understanding. Such a self-assessment tool could enable participants to identify their own learning and use their contributions to discussions to demonstrate that learning, such as by compiling an e-portfolio to showcase their learning to potential employers.

Limitations and Future Directions

This study has limitations. First, the discussion data were collected from an open online course providing learning support (e.g., instructors frequently provided facilitation to guide and

facilitate teachers' social interactions) that was probably greater than many other such courses could offer. This limits the transferability of the qualitative findings to other courses that are less well-resourced. Therefore, future studies can examine the relationship between the quality of discussion prompts and participants' contributions in other open online courses using the Online Discussion Value Framework. Second, study participants were mostly teachers. Researchers may study professionals in other fields (e.g., engineering, management, healthcare) to examine the efficacy of the framework to evaluate the effectiveness of online discussions in supporting professional learning. Third, researchers can apply the framework to the design of discussions in short, closed online courses to test its efficacy in analysing and evidencing social learning among participants.

Declarations

Statement of the Ethics Board Approval.

Permission to collect data from human subjects was approved by Ethics Board at Institute of Education, University College London (REC1607 Online Learning Design Research).

Declaration of interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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Appendix

Themes Related to Discussion Prompts

Themes	Discussion prompts
Encouraging the use of theory to change practice Four discussion prompts were coded into this theme.	Step 3.10 in Run 1; Step 3.11 in Run 2: Limits to what we can do as educators <i>Note:</i> Step 3.10 in Run 1 was renumbered as 3.11 in Run 2 without changing the wording. Can you think of tools, or methods, or channels that can be used to seek support? These could include local government referral systems, professional networks, etc. In the Padlet Support for teachers, suggest some channels, or methods, or mechanisms that could be offered to teachers, and suggest how they might provide support. Double-click on the wall, add your name if you wish, and type in your suggestions. What could be the barriers to a transformative approach to teaching in these challenging contexts? To what extent is it possible to overcome these barriers and promote transformative teaching and learning? Could the tools and methods you have been suggesting help in the process of becoming more transformative? And vice versa? Comment also on what other participants have said.
	Step 4.10 in Run 1: How can digital tools help? Here we look at a learning design that recognises that there are different cultures within a class. It was originally designed for upper primary school learners. Remembering some of the stories you have heard in the course, is the design sufficiently sensitive to work well for all the learners? Your task is to critique the design and adapt it in any way you think would better represent a transformative approach.
	Step 2.4 in Run 2: Applying the Ecological Systems Theory <i>Note:</i> The discussion prompt was re-formulated from Step 2.4 of Run 1. In the last two steps, we have spent some time getting to know the Ecological Systems Theory. In this step, we discuss the way it might apply to your own teaching and learning situations. Given your understanding of the Ecological Systems Theory and its different systems: Think of an example of a difficult situation you have faced with a child in your classroom. Identify what you did to try and improve the situation or support the child. Can you identify which of the systems you acted within in order to change or improve things? Who else (if anyone) did you work or connect with in order to address this difficult situation? Are there other actions that you could have taken within other systems around the child? If so, what are these?

Inviting critical reflection and / or application of theory One discussion prompt was coded into this theme.	Step 2.4 in Run 1: Applying the Ecological Systems Theory In the last two steps, we have spent some time getting to know the Ecological Systems Theory. In this step, we discuss the way it might apply to your own teaching and learning situations. Given your understanding of the Ecological Systems Theory and its different systems: Think of an example of a difficult situation you have faced with a child in your classroom. Identify what you did to try and improve the situation or support the child. Can you identify which of the systems you acted within in order to change or improve things? Who else (if anyone) did you work or connect with in order to address this difficult situation? Are there other actions that you could have taken within other systems around the child? If so, what are these? Add your ideas in the discussion in the following format: One line to describe the situation; What you did; Which of the ecological systems you were working in; Anything else you could have done in the other systems - name the system and what you might have done/or could do in future.
Inviting sharing of experience and reflection Three discussion prompts were coded into this theme.	Step 1.2 in Run 1 and Step 1.2 in Run 2: A challenge for educators As we are working as a community throughout the course, we encourage you to engage with the other participants. You can like and reply to comments made by others that you feel share some aspects of your own experience. (Added in Run 2) Now, think back to when you were a learner rather than a teacher. What was the best teaching and learning environment you experienced? What made it good for you? Share your experience... Step 4.10 in Run 2: How can digital tools help? In this step, 3 digital methods are already used - the <i>FutureLearn</i> course to participate, the <i>Mentimeter Word Cloud</i> to propose and share ideas, and <i>Discussion Forum</i> to discuss them. How do you feel about this and your other experiences of learning using digital methods? Make your comments by responding to at least 2 other comments, as well as creating your own. (Added in Run 2) You can see the learning design of Week 4 here and find out more in the downloads section below.