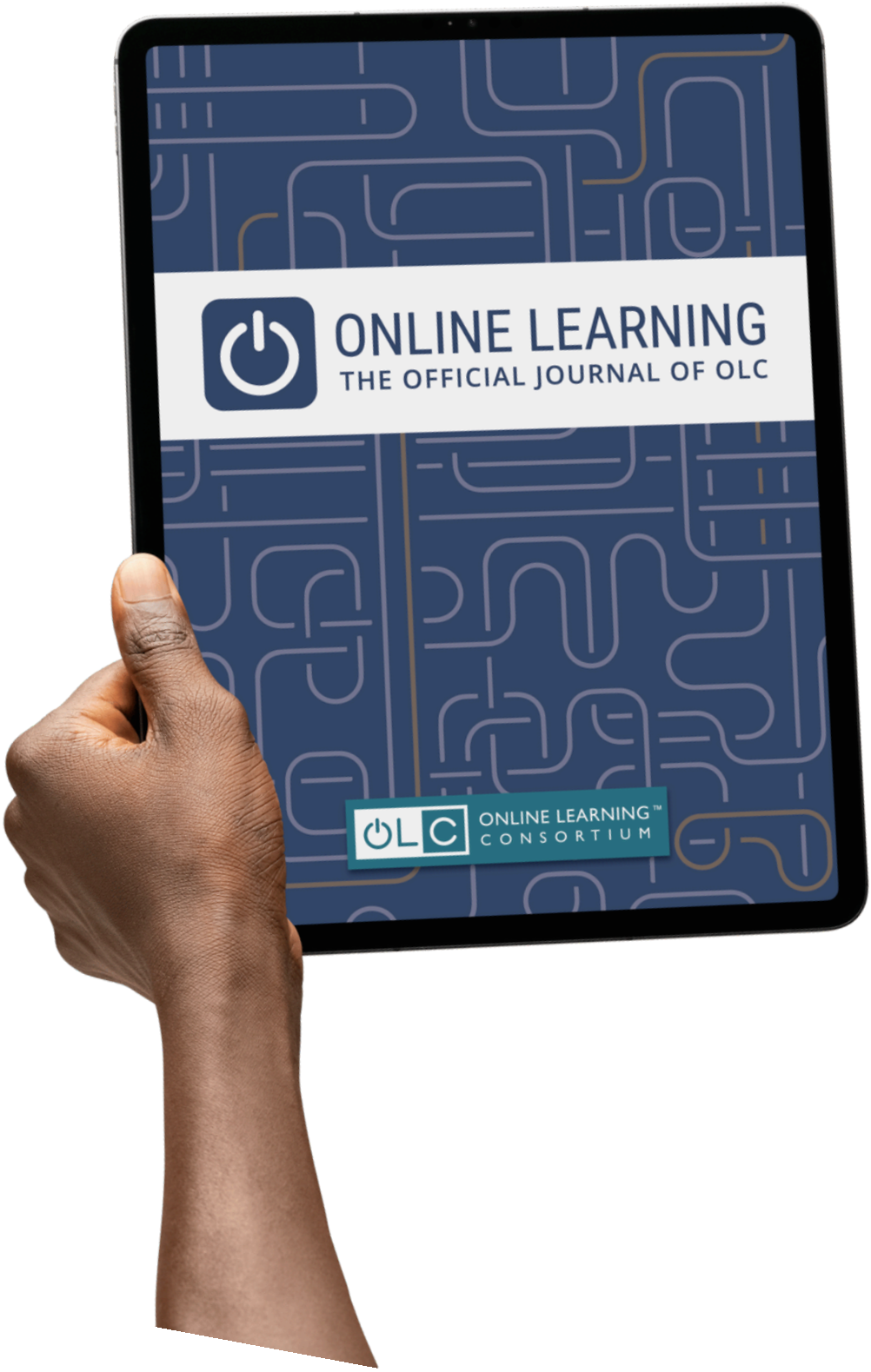

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Editorial: AI, Ghosts in the Machine, and AINT

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As we bring you another issue of *Online Learning* (the third issue of our 30th year of publication, by the way), I wanted again to include some reflections on the topic of AI and academic integrity. As noted by many journal editors, we are seeing exponential growth in the number of AI-generated submissions to journals. Recently, an essay in the Chronicle of Higher Education by Mya Poe and Dylan B. Dryer (2026) noted that the influx of AI-generated papers was degrading scholarship, making it more difficult for authors of papers located in the "missing middle" to attract citations. The essay suggested that, in light of limitations on how AI functions, the literature reviews in AI-generated papers typically include references to a few older seminal papers and establish a superficial connection to this work. The AI-generated work then builds out the literature review with references to very recent papers published in the last two to three years, mostly in lower-quality open-access journals. This is due to the difficulties AI may encounter in gaining access to journals behind publisher paywalls. Because these AI papers are missing high-quality, authentic manuscripts published in the middle years, scholars who have done the hard work of conducting legitimate research and who may need to document their increasing impact through citations are struggling to do so. This missing-middle problem is also a telltale sign that AI was used in the generation of a paper, which should increase editorial scrutiny.

The woes of AI do not end there. Another recent story in the *Chronicle* outlined the next wave of AI-enhanced academic dishonesty. The author, Susan E. Ray, has spent years researching, writing, and conducting faculty workshops on this topic and believed she had found an AI-proof solution to academic integrity issues that also made student thinking and learning visible. Ray had students keep academic journals and versions of class assignments in Google Docs and could therefore monitor the number of edits and the increasing total time spent editing a document. In combination with tools that detected AI-generated text, she believed she had covered all the bases. However, a new entity appeared that promised both to "humanize" the AI-generated text and to take as much time as needed to edit it in Google Docs to make the versioning appear as though a human had typed the assignment. The AI arms race continues, and some faculty report that the only way to foil AI cheaters is to conduct in-class oral exams of students' knowledge, a time-intensive approach that proves difficult to scale to large introductory sections. It might be possible to use collaborative learning and synchronous online environments to address this issue of scalability. One can imagine small groups of students on Zoom, tasked with collaboratively quizzing one another on their understanding of class content, perhaps using rubrics provided to all. This redistribution of assessment could make the idea of oral exams more scalable. The downside is that students generally despise peer evaluations.

This fall I will be teaching an asynchronous online class to pre- and in-service teachers in which we will be reading a new work by Cory Doctorow. In *The Reverse Centaur's Guide to Life After AI*, Doctorow argues that, in automation theory, a longstanding metaphor exists: that of a

centaur. A centaur is a human who is assisted by a technology such that the human benefits in ways they might not in the absence of the technology. A centaur is a human using reading glasses, a hearing aid, or a riding mower, for example. A reverse centaur is a human exploited by technology. For example, Doctorow states that Amazon uses AI to monitor warehouse workers and delivery drivers during their work hours in ways that leave them worse off than if the technology were not used. One example is AI dashboard cameras that check to see if a worker's mouth is moving in violation of Amazon policies against singing on the job. Clearly, most people do not want to become the workhorse of AI. Relying on AI to make important decisions while allocating mundane tasks to fewer and fewer humans appears to be the hoped-for business model at work in the trillion-dollar investments made by AI model builders, according to Doctorow.

This raises thorny questions about our growing reliance on AI both inside and beyond the academy. Research conducted by Michael Gerlich (2025) raises concerns about the relationship between frequent AI use, cognitive offloading, and critical-thinking abilities. The results of the study with 666 participants indicated a significant negative correlation between frequent AI tool usage and critical-thinking abilities, mediated by offloading cognition (or productive struggle) to AI. Another smaller study conducted last year at MIT by Nataliya Kosmyna and her colleagues (2025) found that students using LLMs to assist with writing exhibited underperformance at neural, linguistic, and behavioral levels relative to students who used only their brains or just a search engine. The concerns about developing critical-thinking abilities, the centerpiece of higher education, seem particularly urgent.

The purveyors of LLMs are aware of these concerns and have been working on new tools to avoid the offloading of productive struggle in formal education settings. Grammarly, Google, and OpenAI are developing more Socratic versions of their AI tools, sold to schools as writing aids that will help students through assignments without doing the work for them. A writer for the *New York Times*, Dana Goldstein (2026), tried the products from Google and OpenAI. Initially, they seemed to work, but Goldstein quickly found that the tools were quite willing to provide polished "examples" of prose for a college essay assignment. Company representatives admitted that the tools were works in progress and would require more educator feedback.

We found the same problems last year when a doctoral student, Ed Beck, and I tried to support pre- and in-service teachers in using AI following recommendations from Ethan Mollick (2023) of the Wharton School. Mollick's guidance came in the form of prompts that teachers could use with AI in the role of mentor, coach, tutor, etc., and thus avoid the offloading of productive struggle. However, the teachers we worked with found that, like the efforts described by the *New York Times* author, the prompts resulted in interactions that could be gamed fairly easily. Asking the "tutor" to write an essay, for example, was a hard "no." Again, asking for examples bypassed the support role and produced much the same result as asking for the essay itself. We are hoping to work around this problem with the help of experts working in the field who have addressed this issue with much more sophisticated prompts. One such expert is Anna Mills (2026), who uses Substack to share lessons learned from a grant-funded project, "AI Feedback Customized for Student Writers: The Updated PAIRR." This is a tested library of prompts and instructions that can be shared and reused under a Creative Commons licensing agreement. The overarching goal is to enculturate educators to see AI as a legitimate partner, one in which students are

challenged and supported to work in their Zone of Proximal Development (Vygotsky, 1978), with AI serving as a knowledgeable peer.

Contrast this approach with current concerns (bordering on panic) about the use of agentic AI in higher education. See, for example, an interesting and provocative paper from Bozkurt and his colleagues (2026): "This paper explores the emergence of the 'ghost student': a digital surrogate created by the coupling of Large Language Models (the 'mind') and agentic AI browsers (the 'body'). These entities are capable of navigating Learning Management Systems (LMS), engaging with content, and completing assessments with human-like mimicry, often rendering the actual learner's presence optional" (Bozkurt, 2026, p. 1).

What are the conditions under which a student would elect to forgo all learning and add a "ghost student" to an actual course? Aside from the risks of detection and the clear violation of any principle of academic integrity imaginable, the student is choosing to offload all cognition (and indeed all responsibility) for the course to an AI agent. In this sense, the ghost student represents the logical endpoint of cognitive offloading: AI no longer assists the learner in completing the intellectual work but effectively removes the learner from it. It may represent something beyond even Doctorow's reverse centaur: rather than subordinating the human to the technological system, the ghost student removes the human from the learning process altogether. These developments may appear to constitute an entirely new academic-integrity crisis, but I want to suggest that treating AI as "normal technology" offers a more productive way to understand—and respond to—the problem.

While I will leave a fuller examination of Bozkurt and his colleagues' analysis for another time, the solution they seem to propose is a return to orality. While they acknowledge the challenges of oral assessments and the scaling issue, they do not acknowledge that an entire industry—cybersecurity—works on issues in this domain. While we must admit this is a difficult problem, other sectors (the financial industry comes to mind) have not given up hope. Although many organizations that control and oversee sensitive data constantly confront would-be hackers, the solution has not been a return to paper and pencils but rather the employment of tighter cybersecurity regimes. While it may appear hopeless to do battle with agentic browsers, the answer is not to cede the digital learning field to the academically dishonest (and I don't think that is what Bozkurt et al. are advocating). We may need to investigate new forms of pedagogy, develop new policies, and invest in more sophisticated cybersecurity measures. While this may be a form of war, and we may wish to avoid it, decades of experience indicate that this is simply the new reality with which we must grapple. The need for a combination of new policy, pedagogy, and cybersecurity is more sharply defined by the rise of agentic browsers, but this is familiar ground for many outside of academia. This approach is grounded in the AINT perspective (AI as Normal Technology) of Arvind Narayanan and Sayash Kapoor (2025), outlined in both their book, *AI Snake Oil: What Artificial Intelligence Can Do, What It Can't, and How to Tell the Difference*, and their website, in which they write:

"Now that the collective initial shock of generative AI has worn off, there's a need for structured ways to think about how AI's impacts might unfold, instead of (over)reacting to each new technical capability or emergent social effect."

Again, I don't want to leave the impression that Bozkurt and his colleagues are overreacting. Agentic AI does warrant our full attention, and their article does a commendable service in describing the enormity of the threat. I'm just not sure that the solution is a return to pre-AI days; rather, the authors seem to suggest a program of research on foiling ghost students through minimally technological environments.

However, the appropriate response to increasingly agentic AI is neither an unwinnable detection arms race nor the abandonment of digital assessment. Higher education instead needs an integrated integrity regime combining AI pedagogy that preserves productive struggle, new forms of assessment that verify learning, institutional and course-level policies that define legitimate AI partnership, and a cybersecurity research program aimed at verifying human presence. While AI is indeed a disruptive technology, the AINT framework acknowledges this and suggests that, as with previous disruptive technologies, we will need to adapt.

I want to thank the authors, Assistant Editors, Associate Editors, reviewers, copy editors, and the Online Learning Consortium for their hard work and support, which allow us to bring you the 23 articles in this issue. Also, a big shout-out to our Managing Editor, Carrie Miller, for always going the extra mile to bring you the important work in each issue of *Online Learning*.

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Teacher Perspectives on Challenges and Opportunities for Immersive Virtual Reality Learning Integration in Australian Schools

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Abstract
The impact of using immersive virtual reality (iVR) technologies is well known across the recreational gaming, training, and healthcare sectors. However, iVR's trajectory into education, especially across schooling contexts, is less known and at an early adoption phase. Only a few studies have deeply interrogated the teacher perspective on the benefits of iVR or how it is positioned pedagogically alongside curriculum as a powerful digital learning technology. This article reports on an exploratory descriptive survey of 66 Australian school teachers, two-thirds of whom had experience using iVR in classroom. The survey combined closed- and open-ended questions to elicit teachers' demographic and professional profiles, technical choices, pedagogical applications, perceived benefits, barriers to use, and professional learning needs. Descriptive statistics and thematic analysis were used to compare the perspectives of iVR users and non-users. Findings reveal that early adopters demonstrated innovative pedagogical applications and a strong emphasis on student engagement, while non-users cited cost, access, and curriculum alignment as key barriers. The study provides valuable insights into the enablers and constraints of iVR integration and contributes evidence to inform professional learning, policy development, and scaling strategies in Australian schools.

Keywords: Australian schools, educational technology adoption, immersive virtual reality (iVR), K-12 education, pedagogical integration, professional learning, teacher perspectives

Southgate , E., Unsworth, P., Bower , M., Birt , J., Tafazoli, D., & Cowling , M. A. (2026). Teacher Perspectives on Challenges and Opportunities for Immersive Virtual Reality Learning Integration in Australian Schools. *Online Learning*, *30*(3), 1–23. https://doi.org/10.24059/olj.v30i3.5154

Over many decades, considerable research has sought to understand the adoption of new digital technologies in different educational contexts (Abdelazim et al., 2025; Aldunate et al., 2013; Granić, 2022; Straub, 2009). Several influential theoretical models have been developed to explain adoption patterns, including the Innovation Diffusion Theory (IDT; Rogers, 2003), the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003), and the Technology Acceptance Model (TAM; Davis, 1989). These frameworks remain central to understanding why some educators adopt innovations earlier than others and the conditions under which new technologies are integrated into schools.

IDT suggests that the newness of a technology creates uncertainty for users who seek out examples of effective practice to inform their evaluations (Rogers, 2003). The model posits five adopter categories (i.e., innovators, early adopters, early majority, late majority, and laggards) based on their willingness to engage with an innovation (Rogers, 2003). Early adopters play a particularly important role in education, as they act as opinion leaders and demonstrate how technologies can be pedagogically embedded, thereby influencing wider uptake across schools. TAM and UTAUT/UTAUT2 complement IDT by focusing on the psychological and contextual factors shaping adoption, including perceived usefulness, ease of use, social influence, facilitating conditions, and behavioural intentions. These models have been widely applied in educational technology research to understand the diffusion of innovations such as mobile learning, learning management systems, and more recently, virtual reality (VR) (Açıkgül & Şad, 2020; Geriş & Kulaksız, 2025).

Immersive virtual reality (iVR)—VR mediated by a headset (Slater & Sanchez-Vives, 2016)—has a well-established history of use in training within aviation, defence, mining, construction, and healthcare (Fu et al., 2022; Scorgie et al., 2024). There is growing investment in immersive technologies, with the augmented reality (AR) and VR market projected to be US$50.9bn in 2026 (Statistica, n.d.). While the history of training applications of iVR is relatively well understood, its use in schools sits within an early emergence phase (Southgate, 2023; Schott et al., 2024). As such, theoretical perspectives such as IDT and UTAUT are particularly useful for interpreting the role of early adopter teachers in shaping future directions for classroom integration.

This research invited Australian teachers to share their perspectives on iVR for teaching and learning purposes. Framed as an exploratory descriptive study, its intentions were to (a) investigate the technical choices, pedagogical applications, and experiences of teachers who have used iVR in their classrooms at this phase of early innovation diffusion; (b) compare the perspectives of teachers who have used iVR with those who have not; and (c) explore the implications for scaled adoption of the technology in Australian schools, based on teacher's perspectives. The study contributes to our understanding of the pedagogical integration of iVR in Australian schools, the experiences of early adopter teachers, the professional learning needs of teachers regarding the technology, and insights into scaling up the technology.

Literature Review

VR refers to a 3D computer-generated environment that can be experienced on a computer or mobile device screen, in a CAVE (Cave Automatic Virtual Environment, a room that surrounds the user with projection screens), or through a head-mounted display (HMD), commonly called a VR headset. The term iVR denotes VR mediated through an HMD (Slater & Sanchez-Vives, 2016). HMDs block out stimuli from physical surroundings, immersing users in virtual environments characterised by content stability, persistence, dimensionality,

embodiment, interactivity, and shared or social experiences (Rauschnabel et. al., 2022). Simulated virtual environments can be hyper-realistic or highly imaginative 3D representations and simulations (Grau, 2004).

The attraction to iVR as an educative tool derives from its possibilities to enhance learner sensory experience and sense-making while immersed in virtual 3D worlds (Di Natale et al., 2020). VR offers a set of unique learning affordances that can enhance children's cognition and learning by providing safe experimentation, real-time interactive solo and shared simulations of contemporary places and historical experiences, visualisation of 3D virtual objects for the development of spatial reasoning, representation of abstract concepts, and active learning through constructive creation (Conrad et al., 2024; Dalgarno & Lee, 2010; Pellas et al., 2021). Maas and Hughes (2020) contend that VR games, simulations, and virtual worlds can increase school student's engagement by enhancing curiosity, attention, motivation, interest, and enjoyment. Furthermore, a recent systematic review found that gamified VR is an effective educational tool across all educational levels and subject areas (Lampropoulos & Kinshuk, 2024). Research has also illustrated how school student-created iVR content can stimulate critical and creative thinking through increased collaboration (Liu et al., 2025; Southgate, 2020). For Indigenous students, iVR provides imaginative opportunities to draw on cultural funds of knowledge for authentic learning experiences (MacGill & Unsworth, 2022). A recent report produced by the Immersive Learning Research Network (iLRN) contends that the progressive uptake of immersive technologies in education will play a major role in shaping how educators apply digital learning technologies such as iVR in learning designs aligned to pedagogies that promote authentic learning, creativity, collaboration, and expression (Lee et al., 2020).

However, due to the relatively recent commercial availability of the technology, research on secondary teachers and iVR across national contexts remains in its early stages. A recent study of 137 Belgian teachers who had not used iVR, aimed at identifying factors contributing to their behavioural intention to use the technology, found that while teachers expected iVR to enhance teaching practice, they indicated the need for technical, practical, and pedagogical support (Boel et al., 2023). The importance of teacher support and professional development has been indicated in prior research (see Mystakidis & Christopoulos, 2022). A survey by Khukalenko et al. (2022) of 20,876 Russian educators (representing 7% of the total teacher population) revealed moderately positive perceptions of iVR, with educators in the early stages of integration emphasising the need for professional development and increased technical support.

Further, research points to a range of privacy and safety issues associated with iVR use, especially for children (OECD, 2024; Southgate et al., 2026). Steele et al. (2020) explored U.S. educators' perspectives on the ethical use of iVR applications and the measures they take to protect students' health and safety during VR use. Their study highlighted key concerns, including emotional and psychological safety, social aspects such as personal identity protection, potential physical risks posed by VR headsets, ethical considerations in designing VR scenarios, and the responsibility of teachers to monitor and ensure student well-being. Stranger-Johannessen and Fjørtoft (2021), who collected data from Norwegian teachers identified as early adopters of iVR, underscored the pivotal role of teachers' initiative and confidence with technology in determining the success of integration. Finally, in a systematic review of educational technology adoption, Granić (2022, p. 9739) highlighted the need for more research on "cost-effective/pennyworth" factors related to better understand the most efficient solutions for deploying VR and AR within educational

context with relatively limited budgets. These findings align with theoretical models of adoption such as the IDT (Rogers, 2003) and the UTAUT (Venkatesh et al., 2003), which emphasise the importance of perceived benefits, facilitating conditions, and the leadership of early adopters in shaping diffusion trajectories.

Overall, studies conducted with teachers underscore the early stage of iVR implementation in classrooms and the complexities that early adopters face in negotiating the intricate relationship between technological, ethical, pedagogical, content, and curriculum knowledge required for effective classroom integration. Furthermore, there is a growing need to focus on metacognitive development and fostering creative student output rather than encouraging passive content consumption (Southgate, 2020, 2023; Wei et al., 2025). While research in this area is emerging, there is a relative paucity of detailed classroom use cases. Beck et al. (2023) argue that more research should focus on the actual practices of instructors deploying the technology, a sentiment echoed in a recent OECD (2024) report. Despite these insights, little is known about how teachers who have adopted iVR compare to those who have not, particularly within the Australian K-12 system. The research reported in this paper sought to address the gaps in knowledge about educator practice and professional learning needs with a view to understanding enablers and barriers to scaling up the use of iVR in schools.

Research Design

This research was an exploratory descriptive study. Following Stebbins (2001), an exploratory approach was taken due to the relative lack of research on the phenomenon, in this case, the teachers' perspectives on using iVR in Australian schools. The study was guided by the following research questions:

RQ1. What are the technical choices, pedagogical applications, and experiences of early adopter teachers who have used iVR in their classrooms?

RQ2. How do the perspectives of teachers who use iVR compare to teachers who do not, with respect to rationale, benefits, issues, and professional learning needs?

RQ3. What are the implications of teacher perspectives for scaling up the technology in Australian schools?

Instrument, Recruitment and Ethics

A survey, comprising closed- and open-ended questions, was developed to elicit the experiences and perspectives of Australian teachers who had used iVR in their classrooms (iVR teachers) compared to those who had not used the technology (non-iVR teachers). The survey was based on the Unified Theory of the Acceptance and Use of Technology 2 (UTAUT2) model (Venkatesh et al., 2012), which has previously been applied to pre-service teacher intentions to use iVR in their classes (Bower et al., 2020). The UTAUT2 model includes dimensions relating to performance expectancy, effort expectancy, social influence, facilitating conditions, hedonistic motivation, price value, habit, and behavioural intention. Because of survey length considerations, we included one refined Likert item per dimension, contextualised for practicing teachers. For example, social influence was measured with the item: "I'm influenced by others to use iVR in my classes." While this approach precluded the use of internal reliability testing, the constructs themselves have demonstrated consistent validity in multiple prior studies, including those in VR contexts.

The first section of the anonymous survey comprised questions on demographics (gender identity, age, level of education) and professional background (teaching specialisation, sector, postcode of school or early childhood centre, and current role), and whether teachers had used iVR in their teaching. In the second section of the survey, teachers who had used iVR were asked Likert scale items relating to the UTAUT2 model. Cognisant of the time it would take participants to complete the closed- and open-ended survey questions that followed, only one Likert scale item was used for each of the eight UTAUT2 dimensions investigated, hence construct reliability measures were not applied. However, the UTAUT2 instrument has been validated in numerous educational technology contexts, including for virtual reality, with acceptable to good levels of instrument validity and model fit (Açıkgül & Şad, 2020; Bower et al, 2020; Geriş & Kulaksız, 2025). Teachers who had used iVR were also asked to respond to questions about how they had used iVR in their classes, including the products used, pedagogical applications, learner year level, and reasons for using iVR, along with its perceived benefits and concerns. They were also invited to provide advice for teachers interested in adopting iVR. Non-iVR teachers were asked about their reasons for not using iVR, concerns about the technology, perceived benefits, and enablers for its use, and what they would like to learn about iVR for learning.

Inclusion criteria for the survey were: (1) currently teaching in an Australian early childhood centre, primary or secondary school, or a vocational institution catering to school-aged students; and (2) having either used or not used iVR in the classrooms. Recruitment occurred via social media platforms, including Twitter (now X), LinkedIn, and teacher professional learning Facebook groups. A poster and video containing a QR code link to the survey were posted to these sites by the researchers. The survey was open for completion between 14th of October 2022, and 21st April 2023. The study was approved by the University of Newcastle Human Research Ethics Committee (HREC) (Number H-2022-0307) and subsequently approved by the HRECs of the institutions of other authors.

Participants

Sixty-six teachers participated in the survey, with two-thirds (n=44) having used iVR in their classrooms (the iVR group) and one-third (n=22) being non-iVR users. Across both groups, female teachers made up the largest proportion of respondents. A significant percentage had been teaching for more than 10 years and held postgraduate qualifications, with in the majority serving as classroom teachers. Most were secondary school teachers, while early childhood educators were not well represented—unsurprising, given the safety concerns related to using the technology with young children. Table 1 provides a demographic and professional profile of participants. While the number of participants is below the conventional threshold typically sought for survey research and therefore limits the representativeness and generalisability of the findings, the dataset nevertheless provides important insights into opportunities and constraints identified by teachers who are at the forefront of iVR adoption. These exploratory findings help to characterise the pulse of the iVR movement in Australian schools at this early stage.

Table 1

Demographic and Professional Characteristics of Participants

Demographics and professional profile	iVR group		Non-iVR group	
	n	%	*n*	%

Gender				
Female	25	56.8	17	77.3
Male	17	38.6	4	18.2
Non-binary	1	2.3	1	4.5
Prefer to self-describe	1	2.3	0	0
Age [a]				
25 - 29	0	0	2	9.1
30 - 39	10	22.7	2	9
40 - 49	8	18.2	7	31.8
50 - 59	14	31.8	6	27.2
60+	3	6.8	1	4.5
Highest level of Education				
Bachelor's degree	15	34.1	5	22.7
Graduate diploma/certificate	6	13.6	2	9.1
Postgraduate degree	18	40.9	14	63.6
Other	5	11.4	1	4.5
Teaching level of education				
Primary	4	9.1	11	50
Secondary	36	81.8	11	50
Other	4	9.1	0	0
Years of teaching				
0 - 4	2	4.5	4	18.2
5 - 9	6	13.6	5	22.7
10 - 14	6	13.6	3	13.6
15 - 19	5	11.4	2	9.1
20 - 24	10	22.7	2	9.1
25 + years	15	34.1	6	27.2
School sector				
Early childhood centre (public or private)	0	0	1	4.5
Public/government school	17	38.6	11	50
Catholic school	2	4.5	7	31.8
Independent school	20	45.5	3	13.6
Job role				
Classroom teacher	14	31.8	14	63.6
Head of Department	11	25	2	9.1
ICT integration / digital learning leader	9	20.5	4	18.2

Principal / deputy principal	1	2.3	0	0
Other	9	20.5	2	9.1

[a] Reflects the number and percentage of participants answering the age question with missing data for 9 (21%) of iVR group and 4 (18%) of non-iVR group.

Data Analysis

Researchers utilised both quantitative and qualitative analysis. The researchers employed SPSS 28 to conduct descriptive statistics of the quantitative variables, which involved calculating the frequency and percentage of these variables. The researchers conducted this analysis separately for iVR teachers and non-iVR teachers to provide a comparison of their perspectives. Qualitative thematic analysis was conducted through NVivo 14. To begin, two investigators familiarised themselves with the qualitative data by reading all participant responses to gain a comprehensive understanding of the range of perspectives and experiences expressed by both iVR and non-iVR teachers. Next, two investigators engaged in open, axial, and selective coding processes (Williams & Moser, 2019) to identify, label, and synthesise codes reflecting recurring patterns, concepts, and themes within the dataset. Participant numbers reflecting key themes were counted and are reported, for ease of reading, in rounded percentages with illustrative quotations where appropriate.

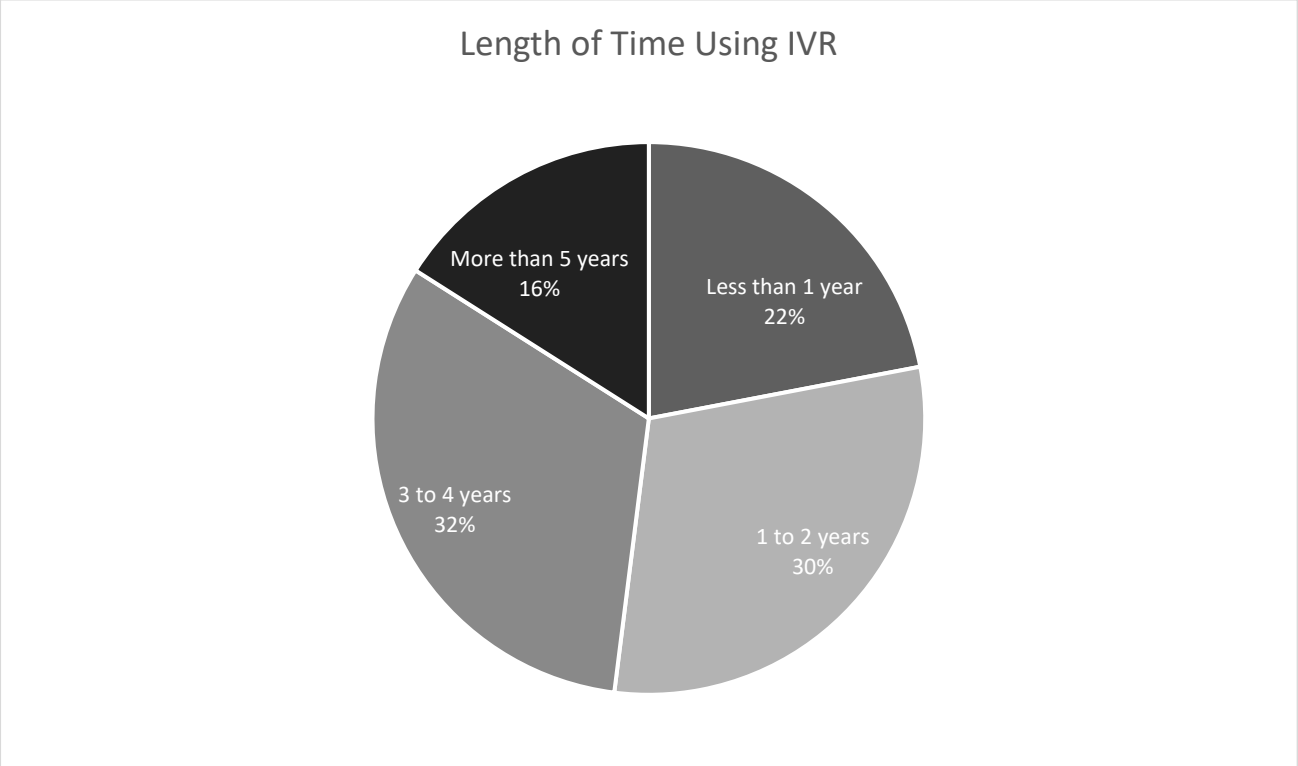
Findings

RQ 1: What are the technical choices, pedagogical applications, and experiences of early adopter teachers who have used iVR in their classrooms?

The length of time that iVR teachers had used the technology in classrooms varied, with almost half having more than 3 years of experience (Figure 1). Forty-one teachers who had used iVR in their classrooms responded to the question, “What iVR hardware and apps have you used or facilitated the use of in the classroom?” From their responses, we categorised headsets according to their potential for three degrees of freedom (3DoF) and/or six degrees of freedom (6DoF). DoF refers to degrees of interaction and navigation or how much a user can move in an immersive 3D environment, enabled by the bodily positional tracking systems built into the VR hardware. Generally, 3DoF provides less interactivity than 6DoF. There was considerable variation in the types of headsets used by teachers (Figure 2), with around 41% having used 6DoF headsets, which are generally more expensive.

Figure 1

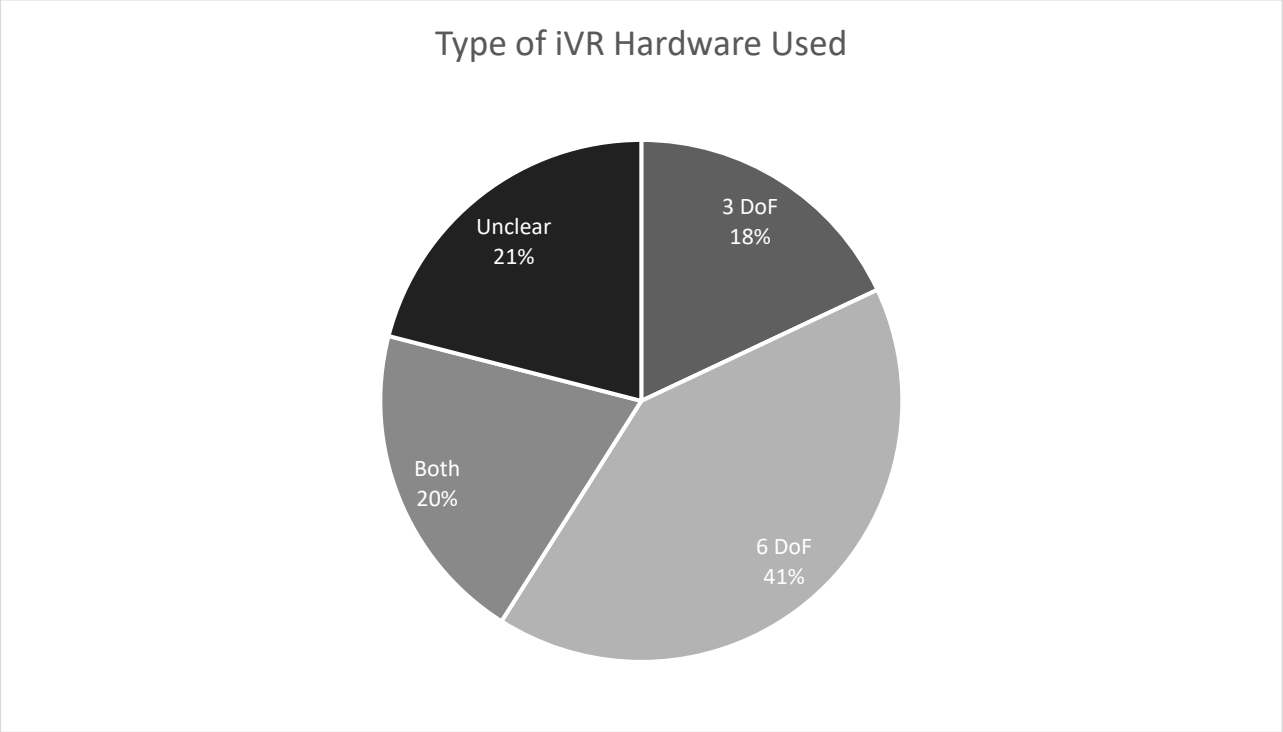
Length of Time Using iVR



Of those who had used 3DoF, most mentioned using smartphones inserted into a VR headset. Of the 6DOF headsets used, 20 respondents specified Meta headsets, eight used HTC headsets, while other headsets were PICO (n=2), HP (n=2), and Lenovo (n=1). One participant mentioned using a CAVE, and one stated they had used a 360-degree camera to produce content. Two participants described going on an excursion to a commercial VR lab, and another described an incursion from a VR company. A range of applications were mentioned, including National Geographic, Space Station, Human Anatomy, and Anne Frank House experiences; CoSpaces; Tilt Brush; Google Earth and Expeditions; and 360-degree videos. One participant mentioned using a game engine to develop content.

Figure 2

Type of iVR Hardware Used



As shown in Table 2, iVR teachers reported an array of pedagogical applications. These included virtual tours and excursions (37%), students as VR content creators (28%), using VR experiences as a stimulus or extension to a lesson (12%), simulation learning (12%), and fostering empathetic learning (9%). It was reasonably common for students to use VR applications to create content that demonstrated their learning (28%). Additionally, iVR was used for research (3%), collaboration (7%), and demonstrations (5%). The technology had been used across various subject areas, including STEM (30%), geography, history, civics and citizenship (21%), media, English, and creative studies (14%), language learning (5%), physical education (5%), and as an extra-curricular activity (7%). Table 2 presents illustrative teacher quotations that demonstrate these pedagogical uses.

Table 2

Teacher Examples of Pedagogical Uses VR

Pedagogical use	Participant quotation
Virtual tours/excursions	"I used it to show some tours of Spain and also the reef environment." "(Used it) for visiting cities overseas and looking at the ancient world."
Stimulus and extension to a lesson	"In English classes using VR panoramas as story starters. Using 360cities as a way to take students to places in novels that students find it hard to relate to then using the experience to improve contextual understanding of the writing craft…"
Simulation	"Had students complete a spacewalk." "Use it for science simulations where expensive equipment is not found in (the) college." "(Use) mechanic/driving simulators"
Empathetic learning	"We opened up learning and social awareness and engagement using virtual reality in class. Empathy for different societies and increased emotional awareness and connection to learning was evident."
Student content creation	"I've generally tried to engage students in creating experiences rather than using prepackaged content." "Their (student) project was to create a school virtual tour using a 360 camera to take photographs of the school." "We are using Oculus headsets in a remote school to tell local stories through art using Tilt Brush."

Teachers generally expressed positive attitudes towards using iVR in their classrooms (Table 3). For example, 95.5% of teachers agreed that using iVR with students was enjoyable, and the majority (90.9%) indicated that they would continue to use iVR in future teaching. Most respondents (70.4%) thought the technology offered good value for money. Additionally, 61.3% agreed or strongly agreed that the technology improved their teaching, and 66% felt confident in using the technology for educational purposes. However, a sizeable minority (25%) only mildly agreed with the latter proposition, suggesting some uncertainty about its educational applications. While most teachers (54.6%) felt they had enough resources to support the use of iVR with students, a sizable minority were either neutral (11.4%) or disagreed (34.1%), indicating variation in the availability of resources to effectively integrate the technology into teaching.

Table 3

Teacher's Experiences and Attitudes Towards Using iVR in Class

	iVR group	
	n	%
Using iVR helps improves my teaching		
Strongly disagree	0	0
Disagree	1	2.3
Mildly disagree	2	4.5
Neutral	5	11.4
Mildly agree	9	20.5
Agree	14	31.8
Strongly agree	13	29.5
I know how to use iVR for education		
Strongly disagree	0	0
Disagree	0	0
Mildly disagree	2	4.5
Neutral	2	4.5
Mildly agree	11	25.0
Agree	20	45.5
Strongly agree	9	20.5
I'm influenced by others to use iVR in my classes		
Strongly disagree	3	6.8
Disagree	6	13.6
Mildly disagree	6	13.6
Neutral	9	20.5
Mildly agree	10	22.7
Agree	5	11.4
Strongly agree	5	11.4
I have the necessary resources and support to use iVR with my students		
Strongly disagree	4	9.1
Disagree	6	13.6
Mildly disagree	5	11.4
Neutral	5	11.4
Mildly agree	9	20.5
Agree	12	27.3
Strongly agree	3	6.8
Using iVR with my students is enjoyable		
Strongly disagree	0	0
Disagree	0	0
Mildly disagree	0	0
Neutral	2	4.5
Mildly agree	8	18.2
Agree	15	34.1

Strongly agree	19	43.2
iVR for educational purposes is good value for money[a]		
Strongly disagree	2	4.5
Disagree	2	4.5
Mildly disagree	2	4.5
Neutral	6	13.6
Mildly agree	7	15.9
Agree	14	31.8
Strongly agree	10	22.7
I'm used to using iVR at school		
Strongly disagree	0	0
Disagree	4	9.1
Mildly disagree	5	11.4
Neutral	7	15.9
Mildly agree	9	20.5
Agree	12	27.3
Strongly agree	7	15.9
I intend to use iVR throughout my teaching in the future		
Strongly disagree	1	2.3
Disagree	2	4.5
Mildly disagree	0	0
Neutral	1	2.3
Mildly agree	6	13.6
Agree	16	36.4
Strongly agree	18	40.9

[a] One participant did not answer this question.

iVR teachers were asked what advice they would give other teachers about using the technology in classrooms (Table 4). The most common and detailed guidance involved the need for teachers to familiarise themselves with the technology before implementation, followed by pedagogical, safety, and professional learning advice. There was also encouragement ("Don't be afraid. Give it a go"). Only one teacher advised not to try iVR, while another advised waiting until it was affordable.

Table 4

iVR Teacher Advice with Illustrative Quotations

Type of advice	Participant quotation
General encouragement (provided by 23% of teachers)	"Go for it—try it and be prepared to learn from the experience." "Give it a go, and don't be afraid to fail forward."
Familiarisation with iVR (trial, test, play, explore)	"Teachers must make time to play in this space to work out how to use VR to develop or enhance student learning….

(provided by 25% of teachers)	Work out what can go wrong before you go into class so that students have a successful experience on the first go." "Make sure you know the space well yourself. Immerse yourself, know the issues."
Professional learning curve (provided by 18% teachers)	"Bring in industry experts or startups to help build staff and student confidence and capability"
	Create a supportive PL (professional learning) network so you are not doing all the hard work alone."
Pedagogical tips (advice from 20% of teachers)	"Start with it in small discrete lesson segments to cement teacher management of the use of the tools, ensure resource development is effective in complementing the use of IVR, and noting what pedagogical style best supports the use of IVR to maximise both outcomes and engagement."
	"Use it in a group work environment where kids cycle through more independent activities so you can work with a small group using VR until they are used to it."
Student safety (advice from 16% of teachers)	"Student safety is more important than innovation, make sure the physical space is conducive to safety. Don't take short cuts here."
	"Always make sure you can see what the kids can see in the headset"
	"Be careful with data sharing. Keep your students safe online."
Cost and investment (advice from 9% of teachers)	"Do your research and talk to other schools before investing."
	"Now in particular, don't rush out and buy the device you like best as it may not work in your school environment."

RQ 2: How do the perspectives of teachers who use iVR compare to teachers who do not, with respect to rationale, benefits, issues, and professional learning needs?

Among iVR teachers, reasons for using iVR technology centered around enhancing student engagement and learning experiences. This meant providing fun, quality, authentic, and creative learning opportunities (98%). Other reasons included curiosity to trial the new technology (18%), benefits of simulation for learning (16%), boost student career aspirations (9%), and interest in professional development (5%). One teacher elaborated on using the technology to provide learning opportunities for students from diverse backgrounds:

> I found my students, who predominantly come from backgrounds where they speak languages other than English, struggled to understand how writers use setting to create meaning for example. The use of VR was able to help illustrate this and then students were able to understand the concept and apply the concept in their own writing. Also, with an increasing focus on exploring multimodal texts using VR provides a unique opportunity to explore the multimodality of VR texts.

Non-iVR teachers primarily identified reasons unrelated to learning for eschewing the technology, with cost and access to funding cited by 50% of this group. Other reasons for not using iVR were lack of access to technology (23%), concerns about curriculum alignment (23%), and time constraints (3%).

Examining the benefits of using iVR for student learning revealed commonalities among both iVR and non-iVR teachers. Both groups identified the enhancement of student engagement (50% of iVR and 37% of non-iVR teachers) and the way iVR could provide opportunities that were not possible for students in the real world (11% VR teachers and non-iVR teachers 14%). The potential of the technology to foster authentic, creative, collaborative, and active learning was acknowledged by both groups (25% VR teachers and non-iVR teachers 27%). A small minority in each group identified using iVR to help students develop technology skills. Both groups raised safety concerns, with 14% of iVR teachers and 10% of non-iVR teachers indicating this was an issue. The iVR group, having direct experience, provided a more nuanced perspective, specifically highlighting COVID-related hygiene concerns (35%) and ethics and privacy issues (5%). Technical challenges, such as school network firewalls, bandwidth limitations, and the need for equipment updates and maintenance, were mentioned by both groups. Unsurprisingly, iVR teachers expressed greater concern over these technical issues (iVR teachers 20% versus non-iVR teachers 9%), given their practical engagement with the technology. Access to resources (cost and appropriate classroom space) and time were also identified as a significant barrier by both groups (iVR teachers 41% and non-iVR teachers 59%). As one non-iVR teacher explained, “Our school funding doesn’t allow for the purchase of these resources and then there is the time needed to ensure it is appropriately integrated into the curriculum and teachers are supported with the implementation.”

There were some commonalities around professional learning needs, with both groups wanting opportunities to explore features of iVR platforms and apps (36% of iVR and 41% of non-iVR teachers). Both groups also emphasised the need for professional development focused on the pedagogical and curriculum aspects of iVR for learning (30% of iVR and 36% of non-iVR teachers). Notably, only iVR teachers highlighted the need for professional learning on safety and ethics (11%) and strategies for integrating the technology at the school level (16%).

Discussion

RQ1. What are the technical choices, pedagogical applications and experiences of early adopter teachers who have used iVR in their classrooms?

The study revealed that teachers who have used iVR in their classrooms were mainly secondary school educators with substantial teaching experience; 82% had over 10 years of experience, and 34% had more than 25 years. Most iVR teachers were familiar with both 6DoF (high-end) and 3DoF hardware, although their use of 3DoF hardware was

pedagogically varied. The majority of iVR teachers expressed confidence in their ability to use the technology, though 25% indicated some uncertainty about its pedagogical value. This ambivalence is understandable given that iVR technology is still in its early adoption phase in schools. This reflects Rogers' (2003) IDT, which suggested that early adopters often balance enthusiasm with uncertainty as they experiment with a novel innovation.

The iVR group had largely positive perspectives on integrating the technology into classrooms compared with the moderately positive perception of iVR from early adopter Russian teachers (Khukalenko et al., 2022). In contrast to Khukalenko et al.'s large-scale findings, which emphasised caution and resource constraints, our smaller sample of Australian teachers demonstrated higher levels of pedagogical experimentation and confidence, suggesting contextual differences in diffusion trajectories. From a TAM perspective (Davis, 1989), this difference may be explained by perceived usefulness: Australian iVR teachers articulated concrete pedagogical affordances, while Russian teachers' evaluations were more tentative. This indicates that perceived usefulness, core to TAM, is strongly shaped by local contexts and opportunities to experiment.

Most participants in our much smaller scale study had developed confidence and technical capability in using iVR and had demonstrated an understanding of its unique learning affordances (Pellas et al., 2021), including but not limited to, student engagement. Their increasing confidence also resonates with UTAUT2's (Venkatesh et al., 2012) construct of facilitating conditions: where institutional support and access existed, teachers were more likely to embed iVR pedagogically.

While iVR was mostly employed in STEM subjects, our teachers also reported its use in creative arts, social sciences, humanities, physical education, career education, and extracurricular activities. This cross-curricular application is like research with early-adopter Norwegian teachers (Stranger-Johannessen & Fjørtoft, 2021). However, unlike Norwegian study, which emphasised teacher enthusiasm in STEM-heavy contexts, our findings reveal evidence of broader cross-disciplinary uptake, including in literacy and cultural education. This suggest that iVR's pedagogical potential may be more expansive than commonly assumed.

Notably, almost a third of iVR teachers used the technology to foster student content creation. This resonates with the call for teachers to move beyond student consumption of pre-packaged content to encourage learners to create and share their own iVR experiences, thereby building mastery and soft skills (Southgate, 2020, 2023). Our results extend this argument by showing that such creative use is already emerging organically among early adopters, highlighting an opportunity for future professional learning to consolidate these practices.

While the survey indicated teacher engagement with a range of iVR applications, there is a need to better understand commonalities and differences in the ways teachers use iVR across subject areas. Future comparative research could examine whether the patterns of adoption we observed (i.e., cross-curricular use and content creation) represent a uniquely Australian trajectory or align with trends in other national contexts. It is also essential to explore how teachers design or weave the technology into the curriculum in ways that leverage the unique learning affordances of the technology for students at different developmental stages and with sociocultural differences. Additionally, further evidence is required on the effects of different design configurations of the technology (e.g., multi-user

environments, interaction modalities, and authoring and generative tools) on the type, size, and growth of learning outcomes, and importantly, student perspectives related to these.

RQ2. How do the perspectives of teachers who use iVR compare to teachers who do not use IVR with respect to IVR rationale, benefits, issues, and professional learning needs?

The main reasons iVR teachers gave for adopting the technology reflected their desire to offer engaging and quality learning experiences. In contrast, non-iVR teachers stated lack of resources, especially the high cost, as the main reason for not using iVR. This contrast underscores a "pedagogical versus pragmatic" divide between the groups: adopters foregrounded student-centred benefits while non-adopters highlighted institutional and infrastructural constraints. Furthermore, this divide echoes UTAUT2's distinction between performance expectancy (adopters emphasising enhanced learning outcomes) and price value (non-adopters foregrounding financial and resource constraints).

Many non-iVR teachers also highlighted the limited access to iVR equipment, with around a quarter expressing curiosity about how iVR could align with the curriculum. Interestingly, both groups identified student engagement as a key benefit of using iVR, recognising its ability to offer unique, immersive learning opportunities that extended beyond the student's real-world experiences. Moreover, both groups recognised the potential of iVR to foster active, authentic, and creative learning. This convergence suggests that while actual practice is uneven, a shared pedagogical vision exists across both adopters and non-adopters, echoing findings from Boel et al. (2023) and Khukalenko et al. (2022), which is also consistent with TAM's focus on perceived ease of use and usefulness: even non-users acknowledged pedagogical potential, but lacked hands-on experience to confirm ease of integration.

This pedagogical focus was reflected in the professional learning needs identified by both groups who wanted opportunities to learn about pedagogical approaches and curriculum design for iVR. Both groups wanted increased access to iVR platforms and apps so that they could explore the pedagogical potential in more depth. Extant literature consistently highlights these types of professional learning needs identified by teachers (Boel et al., 2023; Khukalenko et al., 2022; Mystakidis & Christopoulos, 2022). However, it is worth noting that only iVR teachers explicitly asked for professional learning on safety and ethics, with many demonstrating a clear understanding of the related issues. This insight aligns with other research, such as that by Stranger-Johannessen and Fjørtoft (2021), which points to experienced iVR users being more cognizant of safety concerns.

Furthermore, the practical experience of iVR teachers allowed them to identify more technical barriers to integration in school settings. Although iVR teachers generally viewed the technology as being value for money, both groups cited resources as a key barrier especially cost and to a lesser extent teacher time and appropriate classroom space to operationalise the system in. Taken together, these findings suggest that scaling adoption requires bridging both the pedagogical aspirations of adopters and the pragmatic concerns of non-adopters.

RQ3. What are the implications of teacher perspectives for scaling up the technology in Australian schools?

Scaling up the integration of iVR in Australian schools would require attention being paid to several areas. A key issue involves addressing the professional learning needs of early adopter teachers to further develop their classroom experimentation and innovation with the technology in a safe and ethical manner. This will involve professional learning developed by researchers, industry, and teachers themselves. Interestingly, some iVR teachers in our study wanted professional learning on more broadly integrating the technology across their schools, indicating that scaling up is already part of their thought processes.

Developing communities of practice and mechanisms to showcase the pedagogical and curriculum practice of iVR teachers and their students' learning through the technology is vital if other teachers are to have their questions about integrating an emerging technology into class are to be addressed. This aligns with Rogers' (2003) notion of early adopters acting as role models who reduce uncertainty for the early majority. Our findings reinforce the importance of leveraging early adopters as catalysts for broader diffusion.

For scaling to occur, it is important to develop a low or no-cost systematic program of hardware and software access so that teachers, along with giving them time to familiarise themselves with and explore VR hardware and software in a supported manner. iVR teachers generally thought the technology was value for money. Understanding more about why teachers see value in investing in the technology will be vital in building a case for schools to commit to such a commercially young technology (Granic, 2022). Part of this may be, as Southgate (2020) suggests, challenging teachers' perception that each student requires a headset (1-1 device idea) and instead, designing units of work which weave the VR component into a broader learning sequence that allow a class of students to cycle in and out of a few headsets that are used to enhance specific learning objectives. This does raise the question of needing to know more about the cost, teacher preferences, and efficacy of different models of VR delivery (in-class, VR lab based in school, incursions from commercial companies, and excursions to commercial facilities).

Core to any scaled community of practice or access program will be developing an understanding of how different types of iVR can be used safely and efficaciously in primary as well as secondary schools and outside of STEM subjects. Scaling across the curriculum must include, but reach beyond, technology-focused/rich subjects to encourage teachers in other subject areas to explore technology for their discipline. Research that is embedded in classrooms will be required to develop authentic evidence that deeply considers the needs, geographic and socio-cultural contexts, and interests of school communities in all their diversity. Such an evidence base, which includes rigorous case studies across school subjects with student perspectives foregrounded, will resonate with teachers who might be curious about the technology and encourage them to "Give it a go, and don't be afraid to fail forward."

This was an exploratory study involving a relatively small convenience sample that provided a self-report snapshot of experiences and perceptions. The sample size was not sufficient to be able to generalise effects to the broader population of teachers in Australia or internationally. However, the study did, offer nuanced insights into the early state-of-play of pedagogical integration of iVR in some Australian schools and indicated key barriers to scaling up the technology. As such, it extends the international literature by offering one of

the first comparative analyses of adopters and non-adopters of iVR in schools and provides an empirically grounded agenda for future scaling strategies.

Conclusion

Arguably, the adoption of iVR across schools and higher education in Australia is still in its emergent phase. Those use cases reported vary significantly across schooling demographics, geo-locations, ages, abilities, stages of students, and subject domains. Few studies have deeply interrogated its potential benefits and pitfalls. Some studies have been conducted with teachers to understand their experiences of integrating the technology and, for non-users, their perception of the usefulness of it in school settings. Understanding what enables iVR adoption and ongoing integration and barriers to this is important for addressing the issue of scalability of such a young technology. The present research has sought to address these research gaps by providing a comparative snapshot of Australian teacher perspectives from a user and non-user perspective, with findings largely resonating with the little research that has been previously conducted with educators. Our research has provided a nuanced picture of early adoption pedagogical uses, ethical and safety concerns, issues of access to equipment, funding and teacher time for familiarisation and experimentation, and a range of professional learning needs identified by teachers. While research understandably focuses on iVR learning efficacy, it is vital that the perspective of teachers be harnessed if iVR is to be widely adopted and effectively integrated into school classrooms.

iVR remains a relatively young commercial technology in schools, with research only beginning to capture its educational potential and practical constraints. While existing studies have focused on iVR's efficacy for student learning, this study emphasises the critical role of teachers in shaping the trajectory of adoption and integration. By comparing the perspectives of Australian teachers who have used iVR with those who have not, the study highlights both the enthusiasm of early adopters and the reservations of non-users.

The findings suggest that iVR adoption is currently shaped by a blend of perceived pedagogical benefits, resource constraints, and professional learning needs. Teachers who have engaged with iVR identified opportunities for fostering student engagement, creativity, and cross-curricular applications, but also raised important concerns about ethics, safety, and classroom logistics. Non-users, while recognising the potential value of iVR, were more likely to emphasise barriers such as cost, limited access to equipment, and lack of time for experimentation. These perspectives resonate with international research and can be further explained through established adoption frameworks such as the IDT (Rogers, 2003), TAM (Davis, 1989), and UTAUT2 (Venkatesh et al., 2012), which together underline the importance of perceived usefulness, facilitating conditions, and peer modelling in scaling emerging technologies.

Ultimately, this research offers a nuanced picture of early adoption in Australian schools. It points to clear enablers (including motivated teacher innovators, growing pedagogical confidence, and recognition of student engagement benefits) as well as barriers (such as access, time, and professional learning gaps). The results suggest that scaling iVR in schools will require not only investment in infrastructure and resources but also a systemic approach to professional learning, communities of practice, and ethical guidelines to ensure safe, equitable, and meaningful use across disciplines.

By foregrounding teacher perspectives, this study contributes to the emerging body of evidence on iVR integration in schools and underscores the importance of designing adoption strategies that reflect teachers' realities. As iVR continues to evolve, sustained research and practice partnerships will be essential in transforming isolated experiments into scalable, pedagogically grounded innovations that benefit diverse student populations. These findings provide policymakers, school leaders, and industry partners with practical insights into how iVR can be strategically and sustainably embedded into education systems.

Declarations

Ethics Statement

This study was conducted in accordance with recognized ethical principles and standards. Data were collected with informed consent and reported with respect for confidentiality and anonymity. The study was approved by the University of Newcastle Human Research Ethics Committee (HREC) (Number H-2022-0307) and subsequently approved by the HRECs of the institutions of other authors.

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AI Use Statement

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Conflict of Interest Statement

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

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Student-Content Interaction and Learning Outcomes in MOOCs: The Moderating Role of Self-Efficacy

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Abstract

This study examines how self-efficacy moderates the relationship between student-content interaction and two key outcomes in Massive Open Online Courses: perceived course quality and sustained learning interest. Using survey data from 343 participants in the *Learning How to Learn MOOC* on Coursera, we employed structural equation modeling to test main and interaction effects. Participants were predominantly adult learners with diverse educational backgrounds, balanced gender representation, and varied language backgrounds. Results indicate that student-content interaction positively predicts perceived course quality and sustained learning interest. Moderation analyses further show that the positive effects of student-content interaction are strongest for learners with lower self-efficacy and weaker for learners with higher self-efficacy, suggesting a compensatory or ceiling effect. These findings extend prior MOOC research by empirically modeling self-efficacy as a moderating condition rather than only a direct predictor. Practical implications highlight the importance of designing interactive content and self-efficacy-supportive features to promote engagement in large-scale autonomous learning environments. Limitations include reliance on self-reported data and cross-sectional design. Future research should incorporate objective learning analytics and longitudinal approaches to examine how these relationships evolve over time.

Keywords: Self-efficacy; MOOCs; student-content interaction; online engagement; learning outcomes

Jung, E., Cho, M.-H., Merkebu, J., & Ma, T. (2026). Student-content interaction and learning outcomes in MOOCs: The moderating role of self-efficacy. *Online Learning*, *30*(3), 24-54. https://doi.org/10.24059/olj.v30i3.5420

Massive Open Online Courses (MOOCs) have emerged as a central platform for lifelong learning, offering broad access to learning opportunities for millions of learners worldwide (Loh et al., 2024; Zhu & Doo, 2022). By removing traditional barriers of cost, location, and prerequisite requirements, MOOCs have opened pathways to quality education regardless of learners' geographic or institutional affiliations. As learners from diverse backgrounds engage in MOOCs (Moore & Blackmon, 2022), researchers have recognized that learning experiences, such as how learners perceive the quality of the MOOCs they take and whether they sustain interest in the topics they study, are more meaningful indicators of MOOC success than traditional outcomes such as completion rates (Cho et al., 2025; Long & Liu, 2025).

These two outcomes represent complementary dimensions, one evaluative and one motivational, that reflect both the quality and sustainability of learning in open environments. Perceived course quality reflects learners' evaluations of instructional design, content value, and overall educational experience (Chen et al., 2025; Jung et al., 2019). Sustained learning interest, meanwhile, captures learners' motivation to persist with course content and maintain curiosity over time (Dai et al., 2020; Lee & Song, 2022), a particularly important outcome given that MOOC learners self-direct their participation without external pressures such as grades or tuition investment. Critically, these two outcomes serve as proximal predictors of continued lifelong learning behavior; learners who perceive high quality and maintain interest are more likely to continue taking additional MOOCs for self-directed learning (Moore & Wang, 2021). Yet, our understanding of what predicts these outcomes remains incomplete.

Among the factors that may predict these outcomes, learner interaction with course content is critical given the structural characteristics of MOOCs. Moore (1989) identified three types of interaction in online learning: student-content, student-instructor, and student-student. Of these, student-content interaction is the most consequential in MOOCs. The nature of MOOC environments severely constrains student-instructor and student-student interactions (Alemayehu & Chen, 2023); where hundreds or thousands of learners with different academic backgrounds and living on different continents participate, meaningful exchanges with instructors and peers are not realistically sustained (Loh et al., 2024; Long & Liu, 2025). Moreover, MOOC learners typically do not expect extensive interaction with peers or instructors, recognizing that they enrolled primarily for access to content rather than interpersonal interaction (Gamage et al., 2020). Student-content interaction, the process by which learners interact with and extract meaning from course materials, thus represents the core behavioral pathway through which MOOC learners may develop positive quality perceptions and sustain their interest over time.

While student-content interaction may benefit learners broadly, its effects may vary across learners. Individual differences in self-efficacy may shape how effectively learners capitalize on their interaction with course materials. Self-efficacy, defined as one's belief in their capability to succeed at specific tasks (Bandura, 1997), has been well established as a powerful predictor of learning outcomes (Cheng et al., 2023; Wang et al., 2022). Learners with high self-efficacy approach challenges with confidence, persist through difficulties, and interpret their efforts as productive. In self-directed learning environments such as MOOCs, self-efficacy becomes particularly important because learners must regulate their own interaction with the learning materials without external scaffolding (Cho & Shen, 2013; Kizilcec et al., 2017; Tsai et

al., 2020). However, while prior research has established self-efficacy as a direct predictor of MOOC learning outcomes (Ghali & Amari, 2024), its role as a boundary condition, specifically, whether it amplifies or attenuates the effects of student-content interaction on learning outcomes, remains unexamined.

The present study addresses this gap by examining how student-content interaction relates to two key learning outcomes in MOOCs: (1) perceived course quality and (2) sustained learning interest. We further investigate self-efficacy as a potential moderator of these relationships, exploring whether learners with higher self-efficacy are more likely to show better learning outcomes through content interaction than those with lower self-efficacy. In doing so, this study integrates Moore's (1989) interaction framework with Bandura's (1997) social cognitive theory to offer a deeper understanding of how student-content interaction and self-efficacy jointly shape learning outcomes in a MOOC environment.

Theoretical Framework

This study is guided by two complementary theoretical frameworks. Moore's (1989) interaction framework and Bandura's (1997) social cognitive theory. Moore's framework identifies three types of interaction in online learning, student-content, student-instructor, and student-student, and provides the conceptual basis for understanding how learning occurs in online learning environments. Bandura's social cognitive theory, particularly self-efficacy, provides a cognitive and behavioral lens for understanding why the same interaction behaviors may produce different outcomes for different learners. Together, these frameworks suggest that learning outcomes in MOOCs are shaped not only by what learners do, that is, their interaction with content, but also by the beliefs they hold about their own capabilities, that is, their self-efficacy.

In MOOC environments, student-instructor and student-student interactions are limited due to the scale, asynchronous nature, and learner diversity that characterize these courses (Alemayehu & Chen, 2023; Loh et al., 2024). Student-content interaction therefore becomes the primary behavioral pathway through which learners shape their experience. Research has demonstrated that learners who actively interact with course materials report stronger perceptions of course quality and greater intentions for future learning (Cho et al., 2025; Moore & Blackmon, 2022). These findings suggest that the depth and quality of student-content interaction is a key determinant of learning outcomes and sustained learning interest in MOOCs.

While student-content interaction may be related to positive learning outcomes broadly, self-efficacy theory suggests that the degree of positive learning outcomes may vary across learners. Self-efficacy (Bandura, 1997) has been well established as a direct predictor of learning outcomes in online settings (Cheng et al., 2023; Kizilcec et al., 2017; Wang et al., 2022). However, most studies have examined self-efficacy as a direct predictor rather than as a moderating variable. Differentiating self-efficacy as a direct predictor and as a moderator is critical to better understand students' online learning, as the moderating perspective reveals whether learners with higher self-efficacy benefit more from the same interaction behaviors. Drawing on Bandura's (1997) concept of triadic reciprocal determinism, in which behavior (student-content interaction in this study), personal beliefs (self-efficacy), and environment (the

MOOC context) interact dynamically, we propose that self-efficacy shapes how student-content interaction translates into learning outcomes in a MOOC environment.

Student-Content Interaction and Learning Outcomes in MOOCs

Student-content interaction has been identified as a significant predictor of various learning outcomes in online learning environments. In MOOCs, where learners independently navigate course materials, the quality and depth of their interaction with content directly shapes their learning experience. When learners actively interact with course materials by pausing videos to take notes, attempting practice problems, and revisiting difficult concepts, they are positioned to recognize the coherence and value of the instructional design. Active interaction creates opportunities for learners to appreciate how content is structured, to connect new information with prior knowledge, and to experience the satisfaction of mastering challenging material (Jung et al., 2019; Long & Liu, 2025). In contrast, passive or superficial interaction may leave learners unable to recognize the quality embedded in well-designed content, as they have not interacted deeply enough to extract its value. Chen et al. (2025) found that while content quality positively predicted learning effectiveness in MOOCs, simply providing a large volume of content did not improve learning experiences; MOOC learners' active and meaningful interaction with content determined their learning experiences. These findings indicate that student-content interaction is closely tied to how learners evaluate the overall quality of a MOOC.

Student-content interaction may also play a critical role in sustaining learning interest over time. In MOOCs, where external motivators such as grades, tuition investment, or instructor accountability are largely absent, learners need to generate and maintain their own learning interest throughout the course. Meaningful interaction with content produces cognitive stimulation, the experience of learning something new, solving problems, or gaining insight creates intrinsic rewards that fuel continued learning interest (Lee & Song, 2022). Active interaction also generates a sense of progress and competence; as learners complete modules and master concepts, they experience a sense of accomplishment that reinforces their interest in continuing to learn (Dai et al., 2020). Research on interest development supports these mechanisms. Situational interest, triggered by interacting with stimulating content, can develop into more stable individual interest through repeated positive experiences (Hidi & Renninger, 2006). In MOOCs, learners who interact consistently with course content are more likely to persist through the course and express intentions for future learning (Cho et al., 2021; Moore & Wang, 2021). Based on the theoretical and empirical evidence presented above, we propose the following hypotheses:

H1: Student-content interaction positively predicts perceived course quality in MOOCs.

H2: Student-content interaction positively predicts sustained learning interest in MOOCs.

Self-Efficacy as a Moderator of Student-Content Interaction and Learning Outcomes

Self-efficacy plays a critical role in autonomous learning environments like MOOCs. In traditional classrooms, instructors provide structure, feedback, and encouragement that can partially compensate for low learner self-efficacy. Peers offer social support that helps learners

gauge their progress. These external scaffolds are largely absent in MOOCs, placing greater weight on learners' own self-efficacy beliefs to control their interaction with course materials (Cho & Shen, 2013; Tsai et al., 2020). In this context, we propose that self-efficacy moderates the relationship between student-content interaction and learning outcomes. Specifically, we expect that the positive effects of content interaction will be stronger for learners with higher self-efficacy and weaker for learners with lower self-efficacy.

Regarding perceived course quality, we expect that high-efficacy learners who interact extensively with course content will perceive higher course quality because they approach challenging material with confidence and interpret difficulty as a natural part of learning, which allows them to extract greater value from their interaction with content (Kizilcec et al., 2017; Wang et al., 2022). The same level of interaction may yield smaller gains in perceived quality for low-efficacy learners, who may approach content with anxiety or doubt, interpret challenges as evidence of poor course design or their own inadequacy, and consequently undervalue the learning experience despite having interacted with the same materials. Ghali and Amari (2024) provide initial support for this reasoning, finding that self-efficacy moderated the relationship between interaction and online learning effectiveness. In MOOCs, where learners evaluate course quality based largely on their own interaction experiences without external validation from instructors or peers, self-efficacy beliefs are likely to play an even more prominent role in shaping these quality perceptions.

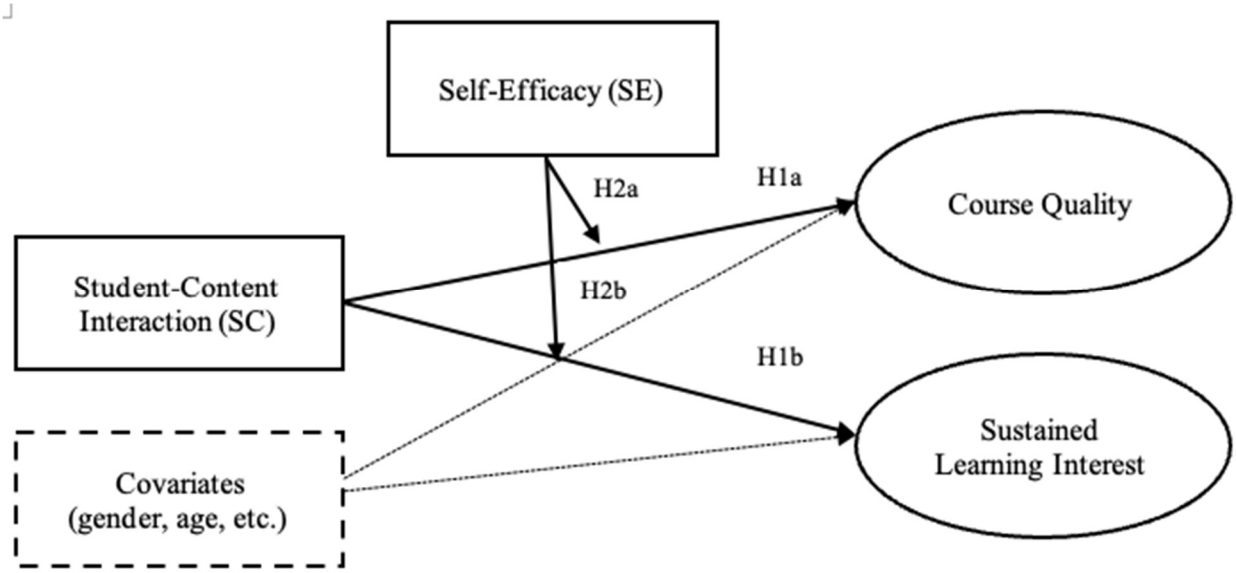
Similarly, we expect that content interaction will strongly sustain learning interest for high-efficacy learners. High-efficacy learners experience interaction with content as rewarding and interpret their progress as evidence of capability, which reinforces their interest in continuing to learn (Cheng et al., 2023; Lee & Song, 2022). When they encounter difficulty, they are more likely to persist and view challenges as opportunities for growth rather than as reasons to disengage. Low-efficacy learners, by contrast, may find that content interaction does not sustain their interest as effectively, particularly if challenges trigger doubt rather than curiosity. Over time, this pattern may widen the gap between high-efficacy and low-efficacy learners, even when both groups interact with the same content at similar levels. Based on this theoretical rationale and supporting evidence, we propose the following hypotheses:

H3: Self-efficacy moderates the relationship between student-content interaction and perceived course quality, such that the relationship is stronger for learners with higher self-efficacy.

H4: Self-efficacy moderates the relationship between student-content interaction and sustained learning interest, such that the relationship is stronger for learners with higher self-efficacy.

Figure 1 presents the conceptual model guiding this study. Student-content interaction serves as the focal predictor of perceived course quality and sustained learning interest. Self-efficacy is positioned as a moderating condition shaping the strength of these relationships. In addition, demographic variables are included as covariates to control for background influences.

Figure 1
Conceptual Model of Self-Efficacy as a Moderator of Student-Content Interaction Effects



Methods

Study Context and Research Design

This study focuses on the self-paced MOOC *Learning How to Learn*, which has been available on Coursera since August 2014. The course aims to equip learners with essential learning strategies based on neuroscience and cognitive science, including chunking, metaphors, and the Pomodoro technique, to help mitigate memory constraints. Structured into four modules, the course is designed to be completed over four weeks. Each module contains ten mandatory videos and two to four optional ones, each approximately 20 minutes long. To assess comprehension, students are required to complete quizzes at the end of each module. The course is led by two instructors, allowing learners to progress at their own pace.

New students can enroll every Monday, ensuring a continuous influx of participants. The course is offered for free, with an option to purchase a Coursera certificate upon successful completion. Instructors maintain engagement through regular announcements and reminders, while also fostering an interactive learning environment by encouraging discussions and reflections on message boards. Even after completing the course, students retain access to materials for ongoing review and learning. Learning How to Learn provides a valuable setting for analyzing the relationship between student motivation, engagement, and their impact on learning outcomes.

We employed a cross-sectional survey design to examine associations among learner motivation, engagement, course quality perceptions, and sustained learning interest within a self-paced MOOC context. A cross-sectional design was selected because the study aimed to capture

learners' retrospective perceptions and experiences following course completion rather than to track changes over time. This study seeks to highlight the role of these factors in shaping the learning experience within self-paced MOOCs, contributing to the growing body of research on online education effectiveness.

Data Collection and Participants

For data collection**,** we used a voluntary convenience sampling approach and invited learners who had completed the *Learning How to Learn* course between 2014 and 2023 to participate in the study, with the final survey response recorded on April 25, 2023. Participants were recruited using a voluntary convenience sampling approach. Eligibility was limited to course completers to ensure that all respondents had sufficient exposure to the course content and learning environment. To enhance participation, the course instructor, Dr. Barbara Oakley, promoted the survey in her weekly *Cheery Friday* newsletter. The survey invitation appeared in three issues, with the last reminder sent in early 2023. This recruitment strategy allowed broad outreach to a diverse learner population while preserving voluntary participation.

Participation was voluntary, and an implied consent was obtained electronically prior to survey initiation. All respondents were informed of the study purpose, their right to withdraw at any time, and the anonymous nature of their responses. No identifying information was collected. Survey data were stored securely and accessed only by the research team for analysis. To enhance data validity, we implemented several procedures, including restricting participation to course completers, removing empty submissions, and screening for incomplete responses prior to analysis. All measures were drawn from previously published instruments or adapted from established scales used in online learning research.

A total of 454 survey responses were received, but 111 submissions contained no data and were excluded. As a result, the final analysis was based on 343 responses. Among these, missing data varied between 1% and 16% across variable. Respondents ranged in age from 16 to 85 years, with an average age of 46.25 (SD = 15.17). In terms of gender distribution, 145 respondents (42.9%) identified as male, while 186 (55%) identified as female. Regarding language background, 175 participants (51.8%) reported English as their first language, while 160 (47.3%) indicated a different primary language. In terms of educational attainment, 28 participants (8%) had a high school diploma, 63 (14.3%) held a college-level degree, 151 (34.3%) had a master's degree, and 34 (7.7%) had a doctoral degree, while 7 respondents (2%) had not completed high school.

Measures

We conducted an anonymous online survey using the Qualtrics platform, which comprised two main sections: (a) demographics and (b) questionnaire. The demographics section collected information about participants' backgrounds (see Appendix A for specific demographic questions), while the questionnaire section focused on self-efficacy, student-content interaction, course quality, and sustained learning interest. In the questionnaire section, participants rated their responses on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Study variables were measured using validated instruments and adapted items aligned with established theoretical frameworks. For each construct, we report the reference source.

Demographic variables were collected as covariates to account for potential confounding effects. Descriptive statistics and bivariate correlations (Table 1) were examined to summarize the data and provide preliminary evidence of construct reliability. The construct validity of key variables is confirmed in this study through a confirmatory factor analysis (CFA) approach within the structural equation modeling (SEM) framework, which demonstrated high factor loadings across the four scales and acceptable model fit (CFI = 0.963; SRMR = .06). See Appendix B for CFA model results.

Course quality.

Course quality was measured using two items adapted from a validated scale assessing learners' self-reported understanding and knowledge gains from the MOOC. A sample item is, *"I feel that I learned a great deal of knowledge in this course."* (Bacon, 2016). Responses were recorded on a five-point Likert scale (1 = Strongly disagree to 5 = Strongly agree), with higher scores reflecting a greater perception of course quality. The mean score for course quality was 4.73 (*SD* = 0.55), suggesting that participants generally reported strong learning outcomes. Prior studies have shown that this scale maintains reliable internal consistency, with Cronbach's alpha values exceeding 0.70. In the current study, the adapted version of the scale demonstrated a reliability coefficient of 0.73. The convergent validity is verified in the Confirmatory factor analysis (CFA) of the SEM model, showing high factor loadings (Table 3 and Appendix B).

Sustained learning interest.

Sustained learning interest was assessed using two items adapted from Oakley, Poole, and Nestor (2016), which explored students' motivation to pursue further learning beyond their MOOC experience. This construct captured both participants' ongoing engagement with the course material (sustained engagement) and their intention to enroll in future MOOCs to deepen their knowledge or skills (future learning intent). The first item measured the former: *"My interest in this course increased over time while taking this course."* The second item assessed future learning intent: *"I am going to take a similar MOOC to extend my knowledge or expertise in the topic."* Participants rated their responses on a five-point Likert scale (1 = Strongly disagree to 5 = Strongly agree). Prior research on MOOC participation has shown consistently high sustained learning interest rates and a strong inclination toward continued learning, with reported sustained learning interest scores averaging 4.55 out of 5.0. In this study, the reliability coefficient for the adapted scale was 0.51, indicating low internal consistency, likely due to the limited number of items capturing conceptually distinct aspects of sustained interest (Streiner, 2003; Tavakol & Dennick, 2011). Accordingly, results involving this construct should be interpreted with caution, as lower reliability may attenuate observed relationships rather than inflate them (Nunnally & Bernstein, 1994). Despite this limitation, confirmatory factor analysis indicated acceptable convergent validity for the sustained learning interest items (see Appendix B).

Self-efficacy.

Self-efficacy was measured using three items adapted from Zimmerman's (2000) framework on self-regulated learning, which emphasizes learners' confidence in their ability to

effectively engage with and master course content. This construct captured participants' perceived capability to understand and apply complex MOOC material. One representative item is: *"I was certain I could understand the most difficult content presented in this MOOC."* Responses were recorded on a five-point Likert scale (1 = Strongly disagree to 5 = Strongly agree), with higher scores reflecting greater self-efficacy. Prior research has established the critical role of self-efficacy in online learning success, linking higher confidence levels to improved engagement and performance in digital education environments. In this study, the mean self-efficacy score was 3.80 (SD = 0.85), suggesting moderate confidence among participants. The adapted scale demonstrated a reliability of .86, suggesting a high internal consistency.

Student-content interaction.

Student-content interaction was evaluated using three items derived from Moore's (1989) framework, which conceptualizes this interaction as the learner's engagement with course materials to build knowledge and track progress. This construct examined the extent to which participants actively interacted with course content and monitored their own learning. A sample item included: *"I monitored my own progress to make sure that I was on the right track in this MOOC."* Responses were measured on a five-point Likert scale (1 = Strongly disagree to 5 = Strongly agree). Previous studies have reported a reliability coefficient of approximately 0.80 for student-content interaction scales, indicating strong internal consistency. In this study, the adapted scale demonstrated a reliability of 0.69, suggesting moderate internal consistency. Because objective learning outcomes such as assessment performance or course completion were not measured in this study, findings related to student–content interaction should be interpreted as reflecting perceived engagement rather than direct learning performance.

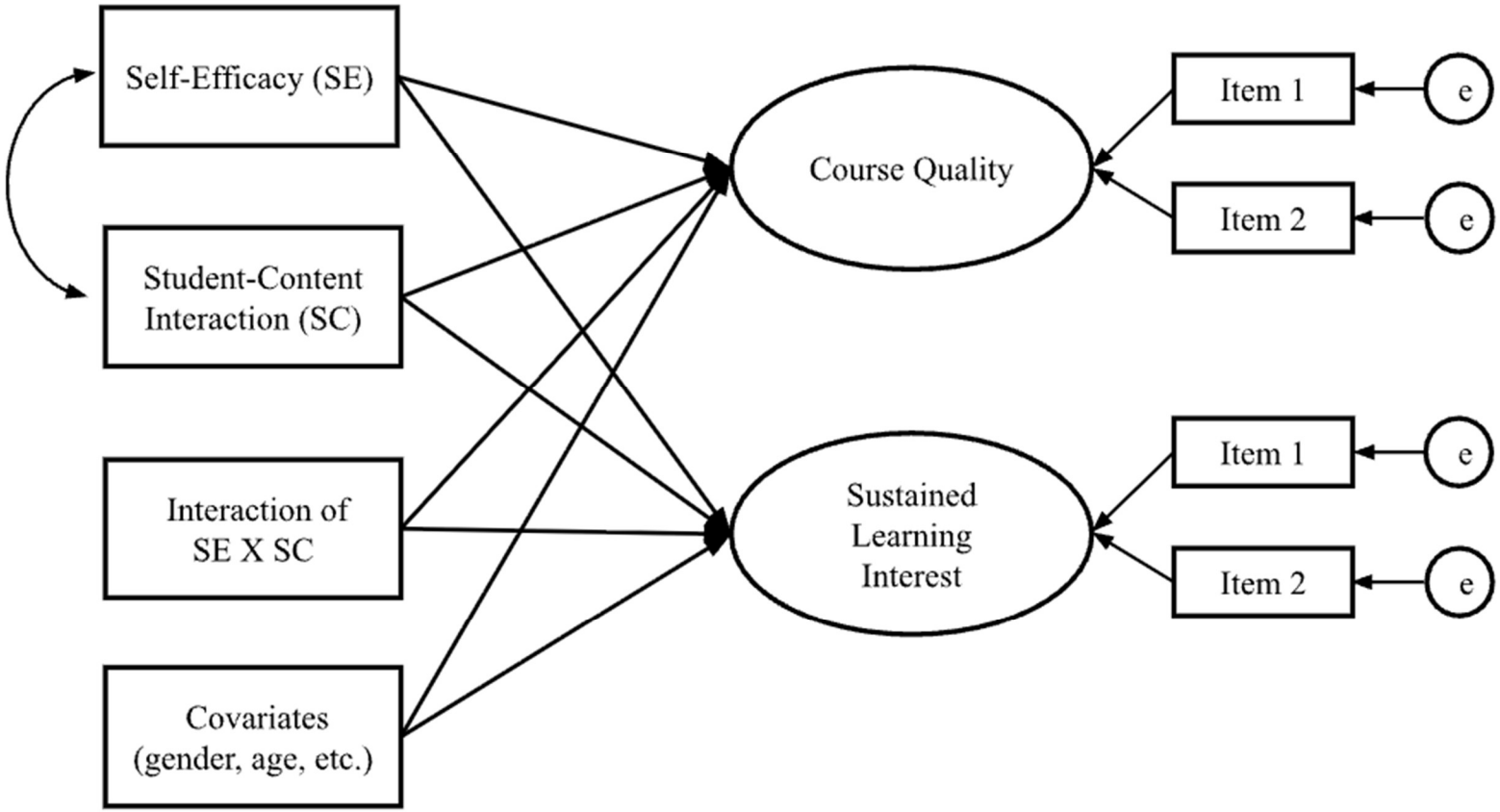
Demographic variables.

Demographic data were collected as covariates to account for potential confounding influences on the study variables. Variables included age (M = 46.25, SD = 15.18), degree (M = 5.09, SD = 1.55, representing varying levels of education), income-education index (M = 15.69, SD = 19.01), gender, ethnicity, socioeconomic status, first-generation college status, and certificate completion. These variables were not examined as focal predictors or moderators because the study was not theoretically grounded to expect demographic differences in the tested moderation effects; instead, they were included as covariates to adjust model estimates for background characteristics.

Data Analysis

We first performed data screening for skewness and kurtosis and computed descriptive statistics (means, standard deviations, correlations) of all variables. To examine whether self-regulation in interaction between student and content moderates the effect of self-efficacy on course outcomes, we estimated in Mplus version 8.0 (Muthén & Muthén) a structural equation model for this study (Figure 2).

Figure 2
Measurement Model of the Key Constructs



Following data screening, we specified and evaluated a measurement model prior to estimating the structural paths. In this model, we specified outcome variables as latent constructs, which included course quality (indicated by two raw items) and student sustained learning interest (indicated by two raw items). Specifying outcome variables (endogenous variables) as latent constructs is important to create unbiased estimators by estimating measurement error and removing it from estimates of variable relations, which can lead to less biased estimates for the outcomes (Spirtes et al., 2001). Although it is ideal to also estimate exogenous variables (the predictors and the interaction variable) as latent constructs (e.g., through a framework of latent moderated structural equations), the current study sample size and thus statistical power is not large enough to support the estimation of a full latent structure model (i.e., the model will be non-identified). Thus, we used observed variables for the predictors (i.e., self-efficacy and student-content interaction) and interaction but kept latent constructs for the endogenous variables (the outcomes). This modeling decision reflects a trade-off between model complexity and statistical power, allowing for more stable estimation of the focal outcomes while avoiding model non-identification. This approach allowed us to maintain statistical power to produce model results while maximizing unbiased estimation for the outcomes.

The model fit was evaluated according to Hu and Bentler's (1998) criteria which included the chi-square statistics, comparative fit index (CFI), the root means square residual error of approximation (RMSEA), and the Standardized Root Mean Square (SRMR). A CFI value of ≥ 0.95, RMSEA value of ≤ 0.06, and SRMR value of ≤ 0.08 would indicate a good fit (Hu & Bentler, 1998). Hu and Bentler recommended that researchers should combine SRMR with another fit index (e.g., CFI or RMSEA) for indication of model fit. We then added structural paths to the measurement model to test if self-efficacy and student-content interaction predicted course quality and student sustained learning interest. Gender, age, ethnicity, education degree, socioeconomic status, first language used, first-generation college student status, and whether receiving a certificate or not were included as covariates to adjust for potential demographic confounding effects.

Missing data is handled by full maximum information likelihood in the model estimation. In addition to estimating the main effects of self-efficacy and student-content interaction on course quality and sustained learning interest, we also examined the moderating effects of student-content interaction by estimating the interaction term between student-content interaction and self-efficacy. Significant interaction terms were interpreted by plotting simple slopes at three levels of the moderator: one standard deviation below the mean (low), at the mean (moderate), and one standard deviation above the mean (high), following established procedures for probing interaction effects (Aiken & West, 1991). Given the number of parameters estimated, we applied Bonferroni adjustment to avoid inflation of type one error rate, such that only p-value significant at $p < .0125$ will be reported as significant.

Results

Preliminary Analysis

Table 1 presents descriptive statistics and bivariate correlations for all variables. Table 2 presents descriptive statistics for the categorical variables. Student-content interaction was positively correlated with self-efficacy ($r = .18$, $p < .01$), and both learning outcomes, including

course quality ($r = .24$, $p < .01$) and sustained learning interest ($r = .26$, $p < .01$). Self-efficacy was also positively correlated with course quality ($r = .23$, $p < .01$) and sustained learning interest ($r = .15$, $p < .01$), and the strongest correlation was observed between course quality and sustained learning interest ($r = .58$, $p < .01$). The demographic variables such as age, degree (level of education), and socioeconomic status did not correlate significantly with any learning outcomes nor with self-efficacy and self-regulation in interaction between student and content.

Table 1

Descriptive Statistics and Bivariate Correlations for All Variable

	Key Variables	Descriptive Statistics				Bivariate Correlations						
		M	SD	N	% Missing	1	2	3	4	5	6	7
1	Age	46.25	15.176	306	9.5	1	.317**	-.265**	0.037	0.035	-0.064	-0.046
2	Degree	5.09	1.554	334	1.2		1	-0.06	0.019	0.105	0.013	-0.098
3	Income-Education	15.693	19.009	322	4.7			1	0.002	0.066	-0.023	0.005
4	Student-Content Interaction	3.8011	0.8514	305	9.8				1	.179**	.242**	.260**
5	Self-Efficacy									1	.232**	.153**
6	Course Quality	4.7333	0.5507	300	11.2						1	.585**
7	Sustained Learning Interest	4.1959	0.7933	296	12.4							1

Note. * Correlation is significant at the 0.05 level (2-tailed).

** Correlation is significant at the 0.01 level (2-tailed).

Table 2
Descriptive Statistics for Categorical Variables

Demographics	Final Sample (N = 338)	
	N	%
Gender		
Male	145	42.9
Female	186	55
Other	7	2.1
Ethnicity		
White	220	65.1
Hispanic or Latino	32	9.5
Black or African American	17	5
Native American or American Indian	1	0.3
Asian/Pacific Islander	33	9.8
Other	32	9.5
Missing	3	0.9
English as First Language		
Yes	175	51.8
No	160	47.3
Missing	3	0.9
First-Generation College Student		
Yes	114	33.7
No	214	63.3
Missing	10	3
Receive Certificate		
Yes	131	38.8
No	205	60.7
Missing	2	0.6

Structural Model

We estimated the structural equation model as the baseline model, in which only main effects were estimated, and no demographic variables were included yet. This baseline model fits the data well, $\chi^2(7) = 2266$, $p = .94$, CFI = .980, RMSEA = .00 [90% CI = .00 to .013], SRMR = .014. In the measurement part of the model, all factor loadings were significant at the $p < .001$ level. We then estimated the conditional model in which demographic variables are included as covariates. These include gender, ethnicity, age, degree, language, status of first-generation students, socioeconomic status, and certificate status; the interaction between self-efficacy and student-content interaction was also estimated to test the moderating effect. The conditional model fit the data well, $\chi^2(29) = 38.16$, $p = .118$, CFI = .976, RMSEA = .038 [90% CI = .00 to .068], SRMR = .032.

The findings of structural paths showed that the latent construct of course quality was significantly predicted by self-efficacy ($b = .18$, $SE = .05$, $p = .001$) and student-content interaction ($b = .14$, $SE = .04$, $p < .001$), meaning that the more student-content interaction and perceived self-efficacy, the higher the perceived course quality outcome. None of the demographic variables predicted course quality. Course quality was also predicted by the interaction between self-efficacy and student-content interaction ($b = -.22$, $SE = .04$, $p < .001$), indicating that the effect of self-efficacy on course quality may be dependent on the level of student-content interaction, and vice versa.

For the latent construct of sustained learning interest, it was not predicted by self-efficacy ($b = .08$, $SE = .08$, $p = .28$), but it was significantly predicted by student-content interaction ($b = .27$, $SE = .06$, $p < .001$), indicating that the higher level of student-content interaction, the higher reported sustained learning interest. Moreover, sustained learning interest was significantly predicted by the interaction between self-efficacy and student-content interaction ($b = -.22$, $SE = .06$, $p < .001$), indicating that the effect of student-content interaction on sustained learning interest may be dependent on the level of self-efficacy. Most demographic variables did not predict student sustained learning interest, except for gender ($b = .23$, $SE = .09$, $p = .019$) and ethnicity, ($b = .52$, $SE = .22$, $p = .021$). Female students reported higher sustained learning interest than male students; Black students reported higher sustained learning interest than White students. Note that these differences are at the marginal level, and they are deemed non-significant after the Bonferroni adjustment.

Together, the model explained 36% of the total variance in course quality, and 34% of the total variance in student sustained learning interest. Unstandardized path coefficients and total R^2s for each model are presented in Table 3.

Table 3
Unstandardized Model Results

Factor Loadings	Estimate	S.E.	P-Value	R-Square
Course Quality				
PL1	1	0	999	0.63
PL2	0.844	0.071	<.001	0.78
Sustained Learning Interest				
SAT1	1	0	999	0.65
SAT2	0.792	0.13	<.001	0.24

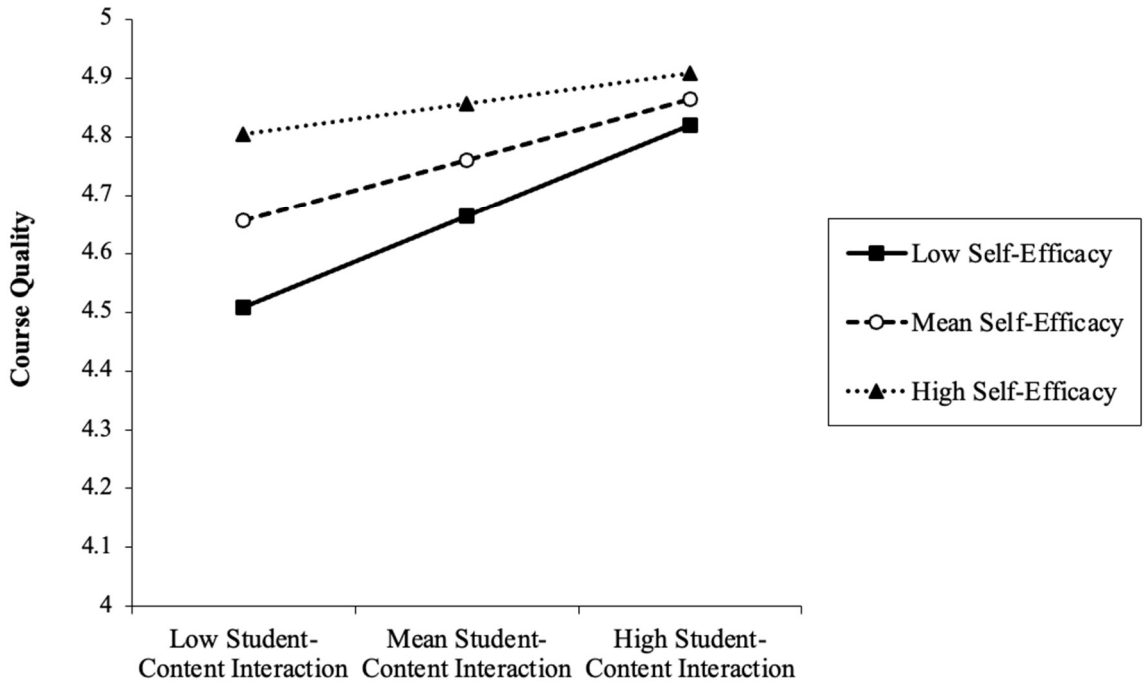
Regression Path	Estimate	S.E.	P-Value	R-Square
Course Quality				0.356
Self-Efficacy	0.179	0.053	0.001	
Student-Content Int (SC)	0.142	0.039	<.001	
Self-Efficacy*SC	-0.221	0.041	<.001	
Gender (M = 1;F = 2)	0.014	0.065	0.832	
Latinx	-0.247	0.12	0.04	
Black	0.023	0.149	0.875	
Asian	-0.088	0.111	0.429	
Other	0.098	0.122	0.424	
Age	0	0.002	0.935	
Degree	0.016	0.023	0.485	
Language	0.138	0.074	0.062	
First Generation	-0.073	0.068	0.289	
Socioeconomic	-0.001	0.002	0.695	
Certificate	0.045	0.066	0.5	
Sustained Learning Interest predicted by				0.336
Self-Efficacy	0.084	0.078	0.28	
Student-Content Int (SC)	0.272	0.058	<.001	
Self-Efficacy*SC	-0.221	0.061	<.001	
Gender (M=1;F=2)	0.231	0.099	0.019	
Latinx	-0.075	0.181	0.678	
Black	0.518	0.224	0.021	
Asian	0.181	0.168	0.282	
Other	-0.077	0.184	0.676	
Age	0.001	0.004	0.865	
Degree	-0.037	0.035	0.287	
Language	0.117	0.108	0.28	
First Generation	-0.031	0.102	0.763	
Socioeconomic	-0.002	0.003	0.358	

Certificate	0.057	0.099	0.568

Moderation Effect

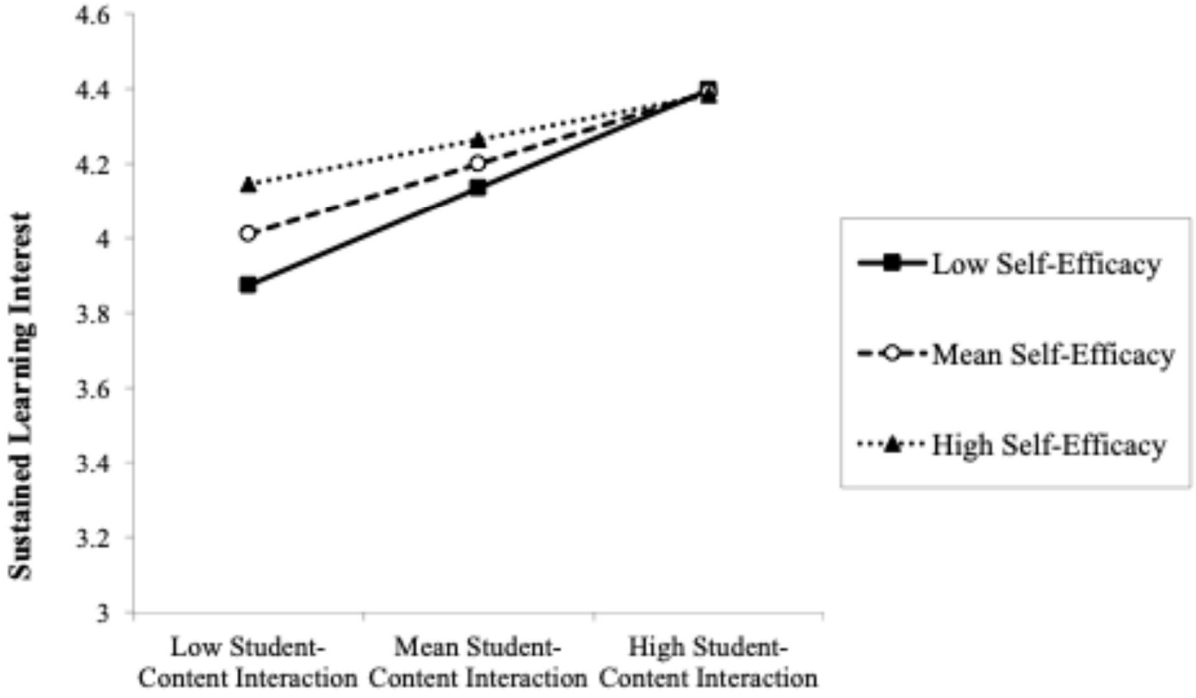
Given that results showed a significant interaction between self-efficacy and student-content interaction on both course quality and student sustained learning interest, we applied simple slope analyses to chart out the interaction effect. As depicted in Figure 3, simple slopes revealed that the positive effects of student-content interaction on course quality were the strongest for students with a low level of self-efficacy (b = .36, SE = .05, p < .001), followed by a weaker association for students with a moderate level of self-efficacy (b = .14, SE = .03, p < .001). The positive effects of student-content interaction on course quality were deemed non-significant for students with a high level of self-efficacy (b =-.08, SE = .05, p = .168).

Figure 3
Interaction Between Self-Efficacy and Student-Content Interaction on Perceived Course Quality



Similarly, as depicted in Figure 4, simple slopes revealed that the positive effects of student-content interaction on student sustained learning interest were the strongest for students with a low level of self-efficacy (b = .31, SE = .08, p < .001). The positive effects of student-content interaction on student sustained learning interest were non-significant for students with a moderate level of self-efficacy (b = .08, SE = .03, p = .28), and not significant for students with a high level of self-efficacy (b =-.14, SE = .11, p = .225).

Figure 4
Interaction Between Self-Efficacy and Student-Content Interaction on Sustained Learning Interest



Discussion

The present study examined the relationships among student-content interaction, self-efficacy, and two learning outcomes in MOOCs. The findings supported the main effect hypotheses that student-content interaction predicts perceived course quality and sustained learning interest. However, the moderation hypotheses were not supported in the expected direction. Instead of amplifying the benefits of interaction, self-efficacy showed a compensatory pattern in which interaction effects were strongest for learners with lower self-efficacy, indicating support for H1 and H2 but not for H3 and H4.

Self-Efficacy as a Predictor of Learning and Sustained Learning Interest

The findings indicate that self-efficacy significantly predicts perceived course quality among MOOC participants but does not directly predict sustained learning interest once student-content interaction is considered. This pattern is consistent with Bandura's (1997) social cognitive theory, which suggests that efficacy beliefs shape how individuals interpret performance and evaluate their learning experience, rather than determining persistence across contexts. Learners with higher self-efficacy reported greater perceived course quality, highlighting the role of confidence as an interpretive lens for judging instructional value; however, sustained learning interest appears to depend more strongly on continued engagement with course materials. This interpretation aligns with Zimmerman's (2000) emphasis on the

motivational and self-regulatory functions of self-efficacy, while also suggesting that in autonomous learning environments, behavioral engagement may be a more proximal driver of ongoing motivation.

While prior research has investigated self-efficacy broadly to online learning outcomes (Rabin et al., 2020; Rodríguez & Armellini, 2017; Wang & Newlin, 2002), its influence may vary across MOOC contexts and outcomes. The *Learning How to Learn* course, which focuses on learning strategies, may attract learners who already feel capable or may foster early mastery experiences that shape quality judgments more than persistence. Future research should examine diverse MOOC subjects and designs to determine when self-efficacy functions primarily as a direct predictor and when it operates instead as a boundary condition influencing how engagement translates into sustained interest.

Student-Content Interaction

The study found that student-content interaction significantly predicted both perceived course quality and sustained learning interest. This result is consistent with interaction theory in online learning, which positions engagement with learning materials as the primary mechanism through which learners construct meaning in large scale asynchronous environments (Moore, 1989). In MOOCs, where instructor and peer interaction are limited, interaction with content functions as the central behavioral pathway shaping learning experience. Learners who more actively engaged with course materials reported higher perceived course quality and stronger sustained learning interest, supporting prior research emphasizing the importance of meaningful engagement for motivation and perceived value (Jung et al., 2019; Moore & Wang, 2021).

Moderating Role of Self-Efficacy

A key contribution of this study is modeling self-efficacy as a moderator of the relationship between student-content interaction and two learning outcomes, perceived course quality and sustained learning interest. The moderation analyses indicate a compensatory pattern. Specifically, the positive effects of student-content interaction were strongest for learners with lower self-efficacy, weaker for learners with moderate self-efficacy, and non-significant for learners with high self-efficacy. This pattern is consistent with the observed negative interaction coefficients and the plotted simple slopes, and it suggests diminishing returns for learners who already hold strong efficacy beliefs.

It is worthwhile to note that these findings diverge from the proposed moderation hypotheses, which assumed that self-efficacy would amplify the benefits of student-content interaction. Instead, learners with higher self-efficacy reported more favorable outcomes overall, yet additional increases in student-content interaction yielded smaller marginal gains for them. For learners with lower self-efficacy, increases in interaction may provide structure and mastery cues that help them translate effort into more positive quality judgments and sustained interest. From a social cognitive perspective, this may reflect differences in how learners interpret difficulty and progress; interactive opportunities can function as confidence-building experiences for low-efficacy learners, whereas high-efficacy learners may sustain engagement even when interaction opportunities are less robust (Bandura, 1997; Zimmerman, 2000).

Implications for MOOC Design

The findings suggest several practical implications for MOOC design and delivery. First, student-content interaction should be treated as a central design lever for supporting perceived course quality and sustained learning interest, particularly for learners with lower self-efficacy. Because the positive effects of interaction were strongest for low self-efficacy learners, designers should prioritize frequent opportunities for active processing that are simple to initiate and easy to sustain across the course. This implication is consistent with interaction theory in distance learning and with evidence that engagement with content is a primary pathway shaping learner experience in MOOCs (Moore, 1989; Jung et al., 2019; Moore & Wang, 2021).

Second, course features that support self-efficacy should be designed as scalable structures rather than individualized services. Although personalized feedback is often limited in MOOCs, designers can still support efficacy through clear weekly goals, progress indicators, low-stakes practice activities with immediate feedback, and prompts that help learners plan and monitor their learning. These features align with social cognitive theory and self-regulated learning perspectives, which emphasize that efficacy beliefs influence effort and persistence, especially in self-directed environments (Bandura, 1997; Zimmerman, 2000; Cho & Shen, 2013; Kizilcec et al., 2017).

Third, the results imply that one design goal is to reduce the early drop-off risk for learners who enter with weaker self-efficacy by lowering the threshold for meaningful interaction. In large-scale autonomous courses, interest is more likely to be sustained when learners repeatedly experience progress through engagement with the material. Therefore, interaction opportunities should be distributed throughout the course and designed to create repeated mastery cues, such as short retrieval practice, worked examples, and brief application tasks that increase in challenge gradually (Bandura, 1997; Dai et al., 2020; Lee & Song, 2022). Based on the present findings, MOOC developers can implement several concrete steps. Early low-stakes quizzes with immediate feedback can create mastery experiences that help low self-efficacy learners interpret effort as productive. Interactive checkpoints embedded in videos can prompt active engagement rather than passive viewing. Short optional practice tasks before higher-stakes assessments can reduce uncertainty and support persistence. Onboarding modules that teach simple planning, monitoring, and reflection routines can strengthen self-regulation and help learners sustain engagement with course materials over time (Cho & Shen, 2013; Kizilcec et al., 2017; Zimmerman, 2000).

Limitations

This study has several limitations. Firstly, the reliance on self-reported data introduces potential biases, as participants' perceptions may not accurately reflect actual learning outcomes (Podsakoff et al., 2003). Additionally, the cross-sectional design limits the ability to infer causality, suggesting the need for longitudinal studies to better understand the evolving impacts of self-efficacy and student-content interaction (Maxwell & Cole, 2007). The study's sample, drawn from a single MOOC, "Learning How to Learn," may affect the generalizability of the findings, given the unique focus and continuous enrollment model of this course (Günther & Witte, 2007). Furthermore, while established scales were used to measure key constructs, they

may not fully capture the complexities of self-efficacy and interaction in a MOOC context (Schunk & Pajares, 2009). Addressing these limitations in future research could enhance the understanding of these dynamics across diverse online learning environments.

Several constructs in this study were measured using a small number of items. Course quality and sustained learning interest were each assessed with two-item scales, which may limit construct coverage and the ability to fully represent the multidimensional nature of these outcomes. Although these items were adapted from prior MOOC research and demonstrated acceptable reliability for exploratory modeling, restricted item sets may attenuate observed associations and reduce precision in estimating structural relationships. Therefore, findings related to these constructs should be interpreted with appropriate caution. Future studies should employ broader multi-item scales to more comprehensively represent course quality and sustained learning interest in MOOC contexts.

Because self-efficacy, student-content interaction, and learning outcomes were all assessed using self-report instruments, the study is subject to potential common-method variance. Learners who report higher self-efficacy may also be more likely to report higher engagement and stronger learning outcomes due to shared perceptual tendencies rather than purely behavioral differences. This may partially inflate observed associations among the study variables. Future research should incorporate objective indicators such as learning analytics, assessment performance, or behavioral trace data from MOOC platforms to complement self-report measures and provide a more comprehensive understanding of these relationships.

Conclusion

This study contributes to ongoing discussions about persistence equity and learner motivation in large scale online learning environments. The findings indicate that student content interaction plays a critical role in shaping perceived course quality and sustained learning interest particularly for learners with lower self-efficacy. This pattern highlights the potential of well-designed interactive content to reduce motivational disparities and support learners who may be more vulnerable to disengagement in autonomous learning settings. By identifying self-efficacy as a moderating condition rather than only a direct predictor the study provides a more nuanced understanding of for whom MOOC design features are most effective. This contribution is particularly relevant for online education practice because it indicates that interactive content design can serve as an equity mechanism by disproportionately supporting learners with lower motivational confidence.

Structural equation modeling showed that student content interaction significantly predicted perceived course quality with $b = 0.14$ $p < .001$ and sustained learning interest with $b = 0.27$ $p < .001$. Self-efficacy significantly predicted course quality with $b = 0.18$ $p = .001$. Interaction effects were significant for both outcomes with $b = -0.22$ $p < .001$ indicating stronger content interaction effects among learners with lower self-efficacy. The model explained 36% of variance in course quality and 34% of variance in sustained learning interest. These insights inform future efforts to design inclusive supportive and motivating online learning experiences that promote persistence and meaningful engagement across diverse global learner populations.

Ethics Approval

This study was reviewed by the Institutional Review Board of the Boise State University (Protocol No. IRB24-102-01) and determined to be exempt from IRB oversight.

Conflict of Interest

The authors declare no conflicts of interest.

Funding

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AI Disclosure

ChatGPT (version 5.0, OpenAI) was used solely for proofreading and grammar refinement. No content generation or data analysis was performed using AI tools.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Disclaimer

The opinions and assertions expressed herein are those of the author(s) and do not necessarily reflect the official policy or position of the Uniformed Services University or the Department of War.

Appendix A

Survey Instrument

Demographics	
Question	Response Type
What is your age?	Open-Ended
What is your gender?	Male Female Prefer not to answer Not listed ( )
In what year did you take this "Learning How to Learn" MOOC?	Open-Ended
What is your ethnicity?	White Hispanic or Latino Black or African American Native American or American Indian Asian / Pacific Islander Other ( )
What is your highest degree?	Less than high school High school graduate 2 or 3 year degree 4 year degree Professional degree/Master's degree Doctorate
How many MOOCs have you taken, including this course?	Open-Ended
Is English your first language?	Yes No
Are you a first-generation college student?	Yes No
By the end of the course, did you receive the certificate or are you expecting to receive the certificate?	Yes No
Self-efficacy	
I was certain I could understand the most difficult content presented in this MOOC I was confident I could learn the basic concepts taught in this MOOC I was certain I could master the knowledge taught in this MOOC	Strongly disagree Somewhat disagree Neither agree nor disagree Somewhat agree Strongly agree
Three types of Interactions: Student-Content	
Before starting an assignment, I planned out my work I monitored my own progress to make sure that I was on the right track in this MOOC I regularly reflected upon what I learned in this MOOC	Strongly disagree Somewhat disagree Neither agree nor disagree Somewhat agree Strongly agree
Three types of Interactions: Student-Student	
I planned my participation in online interaction with other students in advance	Strongly disagree Somewhat disagree

I regularly interacted with other students in this MOOC	Neither agree nor disagree
I regularly checked other students' messages on the discussion board	Somewhat agree Strongly agree
Three types of Interactions: Student-Teacher	
I asked the teaching staff (e.g., instructor, teaching assistant, technical assistant) questions if needed	Strongly disagree Somewhat disagree
I sought assistance from the teaching staff if needed	Neither agree nor disagree
I asked my questions as clearly as possible for effective communication with the teaching staff	Somewhat agree Strongly agree
Course Quality	
I feel that I learned a great deal of knowledge in this course	Strongly disagree Somewhat disagree
I was satisfied with this MOOC	Neither agree nor disagree Somewhat agree Strongly agree
Sustained Learning Interest	
My interest in this course increased over time while taking this course	Strongly disagree Somewhat disagree
I am going to take a similar MOOC to extend my knowledge or expertise in the topic.	Neither agree nor disagree Somewhat agree Strongly agree

Appendix B

Confirmatory Factor Analysis (CFA) of the Scales

Scale Construct	Factor Loading	S.E.	P-Value	R-Square
Self-Efficacy				
Item 1	0.886	0.024	<.001	0.784
Item 2	0.742	0.032	<.001	0.551
Item 3	0.827	0.027	<.001	0.683
Student-Content Interaction				
Item 1	0.605	0.048	<.001	0.366
Item 2	0.857	0.053	<.001	0.734
Item 3	0.534	0.057	<.001	0.285
Course Quality				
Item 1	0.777	0.037	<.001	0.603
Item 2	0.759	0.037	<.001	0.576
Sustained Learning Interest				
Item 1	0.848	0.055	<.001	0.719
Item 2	0.427	0.055	<.001	0.182

Note. Standardized results are presented here. The model fit indices of this CFA is acceptable, with $\chi^2(29) = 65.55$, $p < .001$, CFI = .963, RMSEA = .064 [90% CI = .043 to .085], SRMR = .062.

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Online Teaching in Successive Crisis Contexts: Arab Teachers' Perceptions in Two Emergency Periods

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Abstract
This qualitative study explored 41 Arab-Israeli teachers' perceptions of the transition to online learning during two crises: the COVID-19 pandemic and the Iron Swords War in Israel. Using the Technology Acceptance Model (TAM) as a conceptual framework, the study examined three central dimensions of teachers' use of digital tools: perceived usefulness, perceived ease of use, and intention to integrate digital tools into future teaching. The findings revealed a marked shift in teachers' attitudes and practices, from reactive and constrained adoption during the COVID-19 pandemic to more confident and pedagogically grounded use of digital tools during the subsequent crisis. During the pandemic, teachers experienced significant technological and pedagogical challenges, which limited their perceptions of both effectiveness and usability. In contrast, during the war, accumulated experience enabled more confident and effective implementation of digital tools. While initial adoption during COVID-19 was often reactive and fragmented, the subsequent crisis was characterized by greater pedagogical alignment, increased student engagement, and broader willingness among teachers to embed digital tools into their routine teaching. The study highlights the importance of contextual readiness, sustained professional development, and institutional support in fostering long-term technology acceptance in education.

Keywords: Arab teachers; online learning; educational technology; Technology Acceptance Model (TAM); crisis-based education

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The global outbreak of the COVID-19 pandemic in 2020 and the severe restrictions it imposed triggered an unprecedented transformation in education systems worldwide. Schools were required to shift rapidly to remote learning, delivered through synchronous and asynchronous modalities, including online chat, hybrid models, and video-conferencing platforms (Lestiyanawati & Widyantoro, 2020). In this context, digital technology emerged as an indispensable tool for ensuring the continuity of learning and mitigating educational disruptions (Maatuk et al., 2022; Rasmitadila et al., 2020).

Research has consistently highlighted the pedagogical advantages of integrating digital technologies into education, including the enhancement of teaching quality (Bray & Tangney, 2016; Vasel & Ragonis, 2024), adaptation of instruction to individual student needs, expanded access to learning resources (Pourhossein Gilakjani & Sabouri, 2017), and increased student engagement (Lee et al., 2021; Orlando & Attard, 2016; Schacter & Jo, 2017; Shamir et al., 2017). Technology has also been shown to reshape the teacher's role into that of a facilitator of innovative, student-centered learning (Mishra & Koehler, 2006). Despite these benefits, numerous studies emphasize the difficulties associated with technology integration, variously attributed to teachers' lack of technological proficiency (Simons et al., 2017), inexperience with digital tools (Wood et al., 2005), and most significantly, their perceptions of technology (Adov et al., 2020; Fitzgerald et al., 2023; Scherer & Teo, 2019).

The present study examined how Arab-Israeli teachers perceived the use of digital tools during two distinct periods of emergency remote teaching—the COVID-19 pandemic and the Iron Swords War. Drawing on the Technology Acceptance Model (TAM; Davis, 1989), it explored teachers' perceptions of the usefulness and ease of use of digital tools, as well as their reported willingness to integrate these tools into future teaching practices. By comparatively analyzing retrospective accounts of each crisis period, the study sought to illuminate similarities and differences in technology-related perceptions across successive emergency contexts.

The analysis drew on the Technology Acceptance Model (TAM; Davis, 1989), a well-established and widely used model for explaining individuals' acceptance and use of technological systems in diverse contexts, including among teachers. The model posits that technology adoption is shaped by two central perceptions: perceived usefulness, defined as the extent to which users believe a technology enhances their performance, and perceived ease of use, referring to the degree to which the technology is perceived as requiring minimal effort. These perceptions influence users' attitudes and behavioral intentions to use technology, and these intentions shape their actual integration practices.

In crisis contexts, the conditions under which technology is introduced in education differ from routine educational settings. Emergency remote teaching is often characterized by rapid implementation, limited preparation, and constrained alternatives, rather than by gradual pedagogical planning (Hodges et al., 2020). Under such conditions, teachers' perceptions of usefulness and ease of use become particularly salient for understanding both their immediate engagement with digital tools and their willingness to integrate these tools into future teaching practices. The use of TAM enables a systematic examination of how teachers interpret and evaluate digital technologies when teaching in emergency conditions and how these perceptions evolve across successive crises.

The study sample comprised Arab teachers teaching in Arab schools in the Israeli national education system. The sample was deliberately chosen. Educational structures and

professional conditions in Arab schools are shaped by historical, social, and political factors (e.g., Arar, 2012; Haddad Haj-Yahya & Rudnitzky, 2018; Reingold & Baratz, 2020), causing Arab schools to lag behind their Jewish counterparts in those areas. A crisis is likely to exacerbate existing inequalities, as it will affect teachers' access to resources, institutional support, and capacity to adapt pedagogical practices (Vasel, 2023, 2025b), making the reflections of Arab teachers of particular interest.

Many studies have examined teachers' responses to technology during the COVID-19 crisis (e.g., Orhan & Beyhan, 2020; Rasmitadila et al., 2020). Far fewer have explored how teachers' technology-related perceptions evolve across successive emergency contexts, and to the best of our knowledge, no research has focused on a minority population. This study adds to the literature by examining Arab-Israeli teachers' perceptions at two distinct points, conceptualizing the COVID-19 pandemic and the subsequent war-related disruption as stages within an ongoing process of pedagogical and technological adaptation.

Literature Review

Online learning and emergency learning.

Online learning, defined as "the process of teaching and learning using digital devices designed for this purpose" (Clark & Mayer, 2016), is a pedagogical approach that can take place anytime and anywhere, is adaptable to the learner‘s pace, and is implemented using technological tools. Access to educational tools via Internet connectivity (Cojocariu et al., 2014) enables convenient, short-term learning (Aithal & Aithal, 2016), and there can be a physical distance between teacher and students (Fallatah, 2021).

This pedagogical paradigm became a crucial tool for learning during COVID-19, applied through three primary methods: synchronous learning, asynchronous learning, and a blended approach (Mahoney & Hall, 2020; Richardson et al., 2020). In the synchronous approach, teaching and learning processes occur in real time through the use of online digital tools. In the asynchronous approach, students learn independently without the teacher‘s presence and are sometimes required to submit assignments (Sturm & Quaynor, 2020; Tarman, 2020). The blended approach combines synchronous and asynchronous methods and aims to increase the flexibility of learning processes.

Online learning is a planned process conducted continuously, utilizing advanced digital platforms and tools (Fuchs, 2022). In contrast, emergency learning is an educational approach that operates suddenly and without prior planning, using available technological tools, especially online ones. COVID-19 was one such emergency. Studies conducted during the pandemic noted challenges in online implementation, including lack of knowledge in the field, lack of collaboration among educational staff, and unpreparedness of students, teachers, and parents (Lase et al., 2022). Other factors, such as the lack of resources and insufficient infrastructure, also hindered the implementation of teaching and learning processes using an online approach (Klapproth et al., 2020; Ramij & Sultana, 2020).

Online learning in the Arab education system in Israel.

Although the Arab education system in Israel is part of the general national education system, local policies and politics often impact it. For example, school principals‘ autonomy is often limited (Arar, 2012). They navigate significant pressure from inspectors and local authorities, and their leadership styles are shaped by clan-based political dynamics (Reingold

& Baratz, 2020). Economic factors play a crucial role as well, and Arab schools are under-resourced compared to Jewish schools (Haddad Haj-Yahya & Rudnitzky, 2018). This creates significant disparities between the Arab and Jewish sectors in terms of academic achievements, pedagogical quality, educational services (Abu Asba, 2008), the use of technology in teaching, and teacher motivation (Arar & Massry-Herzllah, 2016).

Dahan et al. (2020) argued this context significantly impacted the preparedness of the Arab education system for emergency remote learning during COVID-19. The number of students (and some teachers) who participated in online learning was limited. Approximately 50% of Arab students were not consistently engaged in online learning. In some areas, there was no online learning at all due to a lack of infrastructure, limited resources, and parental inability to support children in online education. Furthermore, the central technological platform for online learning was not linguistically adapted; it was based on Hebrew and lacked Arabic-language content. Nor was the platform culturally adapted. Arab schools tend to adopt a traditional and authoritarian culture (Vasel et al., 2025), emphasizing rote memorization and imitation and focusing on knowledge transmission. Meanwhile, contemporary educational policies in Israel and globally emphasize creativity, knowledge construction, inquiry, hypothesis testing, and critical thinking (Asbah, 2007).

In Arab-Israeli schools, students are often viewed as passive and lacking the right to express independent opinions or positions (Vasel et al., 2025), while the teacher is an authoritative figure who makes the decisions (Vasel et al., 2025). Many teachers adhere to traditional teaching methods and do not implement innovative learning strategies (Vasel, 2025a; Vasel et al., 2025). Research examining hybrid learning (a combination of online and face-to-face learning) during COVID-19 pointed to the reflection of the patriarchal and authoritative nature of Arab society in the adoption of traditional teaching methods, limited autonomy granted by school principals, and the underdevelopment of digital skills among teachers (Habiballah et al., 2021).

Teachers' pedagogical beliefs and attitudes towards technology.

The pedagogical approach teachers adopt in the classroom is derived from their pedagogical beliefs (Fives & Gill, 2014; Vasel, 2025a; Vasel et al., 2025). Accordingly, to assess the success of pedagogical innovation in teaching, particularly innovation based on a constructivist approach, it is essential to understand teachers' beliefs and perceptions (Liu, 2011; Sang et al., 2010; Vasel, 2025c; Vasel et al., 2025). For example, teachers who embrace a constructivist pedagogical approach, focusing on student-centered learning and the integration of technology in teaching, tend to use digital tools more than those who adopt a traditional pedagogical approach, where the student is viewed as passive and the teacher is the central figure in the classroom (Tondeur et al., 2017).

Teachers' attitudes towards technology significantly influence the success of its integration into teaching (Greer et al., 2016; Hsu, 2016; Tondeur et al., 2017). Studies show that teachers with a positive attitude towards technology are more likely to use digital tools in teaching (Demirci, 2009), believe in the importance of integrating technology into teaching, and can cope with the technical challenges (Ertmer et al., 2012).

TAM (Davis, 1989) seeks to understand why some users perceive certain information systems positively while others resist using them. The model suggests users' attitudes and subjective norms influence their intentions, and these intentions, in turn, predict their behavior. According to TAM theory, understanding the acceptance or rejection of an

information system requires focusing on two main perceptions: perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which users believe using a particular information system will enhance their performance, while perceived ease of use refers to the expectation that using the system will require minimal effort.

The Present Study

Research objective.

The objective of this qualitative study was to investigate Arab-Israeli teachers' perceptions of the transition to online learning during two distinct crisis periods—the COVID-19 pandemic and the Iron Swords War—using TAM as a theoretical framework. More specifically, it examined teachers' perceptions of usefulness and ease of use of digital tools at two crisis points and their willingness to integrate them into their teaching practices.

Research questions.

1. How did Arab teachers perceive the usefulness and ease of use of digital tools during the COVID-19 pandemic and the Iron Swords War?

2. In what ways did these two crisis periods influence Arab teachers' willingness to integrate digital tools into their future teaching practices?

Methodology

Participants

The study involved 41 Arab teachers and two distinct crises. First, in 2023, 23 teachers were asked to reflect on their use of technology during COVID-19. They taught in 20 schools within the Arab community, located in the Haifa and Northern districts; 15 were women and eight were men. Eleven taught in elementary schools, eight in middle schools, and four in high schools. All taught core subjects, including languages, mathematics, and sciences. Second, in 2025, 18 teachers from the Northern District were asked about their use of technology during the 2024 Iron Swords War. This group consisted entirely of women. Ten elementary school teachers were from five schools, with two teachers representing each school. The remaining eight teachers were from three secondary schools; two teachers from one school and three teachers from each of the other two schools.

The Northern District was selected because of the researcher's residence in the region and her professional access to teachers in the Arab education system. In addition, in 2024, the Northern region experienced sustained security-related problems leading to the closure of schools and a full transition to online learning. This context was therefore relevant for examining teachers' experiences of emergency remote teaching in two crisis period.

Participants were recruited using a convenience sampling method based on accessibility (Richards & Morse, 2012). For the second period, the researcher also employed a snowball sampling method. Each teacher who agreed to be interviewed was asked to recommend at least one colleague from the same school who might be willing to participate. This approach ensured that at least two teachers from each school were involved, enriching the perspectives collected from each institution.

To be included, teachers had to be working in the Arab education system in Israel and to have taught during both periods of interest. Teaching experience and levels of digital literacy were not used as inclusion or exclusion criteria.

A recruitment call was published and disseminated through school administrators and pedagogical instructors in both periods. Teachers who agreed to participate filled out an online questionnaire that included their details and three suitable times for an interview.

Research Tools and Data Collection

Data were collected in semi-structured interviews to facilitate comprehensive information gathering. While a list of questions was prepared in advance, the order of questions was adaptable, allowing flexibility based on the dynamics of the interview, the characteristics of the interviewee, and the depth of responses. This approach enabled the introduction of additional questions as needed, eliciting thorough and rich insights (Wimmer & Dominick, 2013).

To ensure trustworthiness in the data collection and analysis phases (Holstein & Gubrium, 2021; Kornbluh, 2015; Thornberg & Charmaz, 2014; Willig, 2014), the level of detail in the interview questions was scrutinized by an independent expert specializing in the study‘s subject matter. The questions were subsequently translated from Arabic, the participants‘ native language, into Hebrew and evaluated by external researchers with expertise in relevant issues in Arab society, thereby ensuring their reliability and accuracy.

The interview questions were designed to explore teachers‘ attitudes towards online remote learning, focusing on the perceived usefulness and ease of use of technological tools during the two crisis periods. Participants interviewed after the COVID-19 period and those interviewed after the war constituted two distinct groups. The interviews were conducted shortly after the relevant crisis period. Each participant was interviewed once. Participants were invited to reflect on their experiences during the crisis. Participants at the second time point were also asked to reflect on how their experiences during COVID-19 affected their wartime experiences.

All interviews were conducted in the participant’s native language, fostering a personal and direct interaction between interviewer and interviewee. Each interview lasted a minimum of 45 minutes. To accommodate crisis-related restrictions and minimize participant burden, most interviews were conducted via video conferencing (using Zoom) in the afternoon or evening. Notably, while the majority of teachers expressed a preference for online interviews, two participants requested face-to-face meetings; these were arranged at a community center that graciously hosted them. All interviews were recorded and transcribed for subsequent analysis.

Data Analysis

The interview questions were not structured explicitly around TAM, but the model was used as an analytical lens to interpret teachers’ accounts. Themes emerged inductively from the interview data and were mapped onto the three TAM dimensions—perceived usefulness, perceived ease of use, and intention to integrate digital tools—in relation to the study’s research questions. Questions addressing perceptions of effectiveness, motivation, and perceived drawbacks were analytically associated with perceived usefulness; questions focusing on challenges, skills, and manageability were linked to perceived ease of use;

questions concerning future integration and school-level preparedness were interpreted in relation to teachers' intention to integrate digital tools into their future teaching practices. Appendix A presents the interview questions and illustrates their alignment with the research questions and TAM framework.

Data were analyzed using inductive qualitative content analysis (Cho & Lee, 2014), following the six phases of thematic analysis outlined by Braun and Clarke (2006): familiarization with the data, generation of initial codes, identification of potential themes, review of themes, definition and naming of themes, and development of the final thematic structure. The coding process was conducted by the researcher through an iterative cycle of open coding and constant comparison across interview transcripts. Initial codes were derived inductively from the data and continuously refined through repeated engagement with the transcripts. Themes that emerged inductively from the data were mapped onto the TAM constructs to support theoretically grounded interpretation while preserving the integrity of participants' accounts.

A multiple-case study design was employed (Yin, 2014), treating each period (COVID-19 and the war) as a distinct case. Within-case analyses were conducted separately for each period, followed by a cross-case comparison aimed at identifying similarities and differences between the two crisis contexts. This cross-case comparison was conducted by systematically examining patterns across themes in relation to the three TAM dimensions.

Established qualitative research practices were applied to enhance the trustworthiness of the findings, including repeated and careful reading of transcripts and systematic analysis of the data (Alshenqeeti, 2014). Credibility was supported through sustained engagement with the data, dependability through consistent application of the analytical framework and documentation of analytic decisions, confirmability through reflexive analysis and data-grounded interpretations, and transferability through detailed contextual description.

Although coding was conducted by a single researcher, analytic rigor was supported through systematic documentation of coding decisions, iterative re-examination of codes and themes, and consistent application of the analytical framework across cases. Formal member checking, peer debriefing, and triangulation were not employed.

Ongoing reflexivity was maintained throughout the analytical process, with attention to the researcher's positionality and potential interpretive biases. The researcher's professional background and familiarity with the educational context were considered factors that might shape the research process. To address this, reflexive analysis was maintained, and interpretations were carefully grounded in participants' accounts rather than in prior assumptions.

As the interviews were conducted in Arabic and reported in English, particular attention was given to language validity. The researcher, fluent in Arabic and English, conducted the translations and systematically reviewed all translated excerpts against the original transcripts to ensure semantic accuracy and contextual equivalence. This cross-language verification process aimed to preserve the intended meanings of participants' statements and minimize the risk of interpretive distortion. At the end of each interview, participants were given the opportunity to clarify, refine, or expand their responses, thereby supporting the credibility of the data and their interpretation (Creswell & Creswell, 2017).

Data analysis continued until no new themes emerged within or across the two cases. In interpreting the findings, the reflective nature of the interviews was taken into account and data were interpreted with caution.

Ethical Considerations

The study received approval from the Chief Scientist of the Ministry of Education and ethical clearance from the institutional ethics committee prior to data collection. Participation was voluntary, and informed consent was obtained from all participants. Participants were informed about the purpose of the study and their right to withdraw at any stage without consequence. Confidentiality and anonymity were ensured by removing identifying information from the transcripts and using pseudonyms in all reports. All data were stored securely and were accessible only to the researcher.

Results

The findings are presented in two stages: first, findings for each of the two crisis periods (within-case analysis), and second, comparative findings (across-case analysis).

Within-Case Findings

Case 1: COVID-19 pandemic.

(1) Perceived Usefulness. Teachers described the transition to online learning during the COVID-19 pandemic as both disruptive and transformative. While the shift was sudden and unplanned, many saw significant benefits in using digital tools for instruction. Teacher Hassan stated, “The shift gave us a reason to rethink everything. We found ways to make lessons more interactive and relevant.” Similarly, Teacher Doaa emphasized, “Moving to online platforms improved the way I delivered content; it became easier to reach all students.”

Several teachers noted improvements in student engagement and autonomy. Teacher Leen shared, “Before the pandemic, my students were passive. Online learning made them more responsible and engaged.” Teacher Azl observed, “Digital tools helped students who were usually quiet to participate more. I saw them come to life during Zoom discussions.”

Others emphasized the pedagogical innovation it enabled. Teacher Mayan explained, “It allowed me to try things I never had time for before, like project-based learning and peer reviews.” According to Teacher Adam, “We finally entered the 21st century. I felt like I was teaching skills that actually matter.” Some teachers linked it to their students‘ development of broader life skills. Teacher Sona said, “Students learned to manage their time, communicate better, and ask questions more clearly.” In this sense, digital tools were seen not only as instructional aids but as mechanisms for personal growth.

Still, teachers clarified that perceived usefulness was conditional. Teacher Sawsan noted, “It works, but only if there’s support. Without training, it’s overwhelming.” Teacher Ibrahim added, “There’s no point in having great platforms if the teacher doesn’t know how to use them effectively.” Importantly, while teachers saw potential in the tools, many emphasized that the initial transition was chaotic. Teacher Eden reflected, “It all happened too fast. We didn’t have time to explore or test anything; we were just thrown in.” Even so, some

viewed the disruption as a necessary catalyst. Teacher Areen concluded, “We wouldn’t have changed without the pandemic. It forced us to move forward, even if the process was messy.”

(2) Perceived Ease of Use. While some teachers adapted quickly to online teaching platforms, others found the experience difficult and stressful. Technological barriers were a common theme. Teacher Sime said, “Learning the systems while also teaching was exhausting. I felt like I was always behind.” Teacher Mervat added, “Every new app came with new problems. I spent more time troubleshooting than teaching.” Access inequality also played a significant role. Teacher Abed explained, “Many of my students didn’t have stable Internet. I couldn’t reach everyone.” For others, emotional and relational aspects of teaching were harder to replicate online. Teacher Soha said, “I missed the energy of the classroom, the smiles, the body language.” Teacher Rana noted, “I couldn’t tell who was following and who was lost. It felt like teaching in the dark.”

Despite the challenges, some teachers found ways to adapt and were positive about the experience. Teacher Amna said, “Teaching from home gave me flexibility. I could plan better and focus more without distractions.” Teacher Mahmod echoed this, saying: “Some of my students who struggled in class found it easier to engage from home.” Teacher Salma shared, “We created group work via shared documents, which helped restore a sense of collaboration.” Teacher Adam observed, “Recording lessons helped students review at their own pace, and it helped me reflect too.”

The main consensus was that ease of use improved over time, but only with support. Teacher Reem remarked, “Once we got training, things became manageable. But the start was too abrupt.”

(3) Intention to Integrate Digital Tools in Future Teaching. Teachers were divided in their long-term commitment to using digital tools after the pandemic. Those who had positive experiences expressed enthusiasm. Teacher Areen said, “I’m definitely going to keep using online platforms; it opened up new ways to connect with students.” Teacher Soha explained, “Technology won’t replace face-to-face teaching, but it adds value. I plan to use both.” Teacher Hassan offered a balanced view: “I’m not abandoning traditional methods, but I now have more options. I can mix and match.” Teacher Sawsan agreed: “I’ll keep what worked and leave what didn’t. Some tools really improved student engagement.”

Not all teachers shared this optimism. Teacher Leen admitted, “It didn’t work for me. It felt disconnected and ineffective. I’ll probably go back to the old ways.” Teacher Aml added, “If the tools don’t make teaching better, there’s no reason to keep them.” The variation in intention often depended on the teacher’s personal experience, access to resources, and perceived success. Teacher Ali commented, “Using platforms for homework and grading saved me time; I’ll definitely continue that.” But Teacher Seham said, “The learning curve was too steep. I’d rather not go through that again.” Teacher Morad raised concerns about student access: “It’s not fair if not all students have devices or internet. That has to be fixed before we make it permanent.”

Despite skepticism, many teachers expressed a newfound openness to pedagogical experimentation. Teacher Rana concluded, “Now that I’ve tried new methods, I’m not afraid to try more. That’s a big shift for me.”

Case 2: Iron Swords War.

(1) Perceived Usefulness. Teachers who engaged in online teaching during the wartime crisis had more favorable and confident perceptions of the usefulness of digital tools, shaped by their prior experiences during the COVID-19 pandemic. Teacher Roz explained, "This time, we knew what we were doing. We had strategies, tools, and confidence." Teacher Eden stated, "During COVID, we were lost. Now we're prepared. I adjusted my materials in a day and was ready to go." Teacher Areej added, "I reused the digital content I developed earlier; it saved time and worked even better the second time."

The usefulness of digital tools was especially evident in maintaining learning continuity under stress. Teacher Maha said, "The platform allowed me to keep my students focused despite the fear and uncertainty around them." Teacher Nawal reflected, "My students said our sessions were a kind of escape. That made it feel worthwhile." Teachers also emphasized how online learning supported differentiation and independent learning. Teacher Huda noted, "I tailored materials to different levels easily. Students worked at their own pace, and it worked well." Teacher Dima added, "It helped students who usually stay behind to actually succeed. That was new for me."

Some identified institutional benefits. Teacher Walaa shared, "Parents were impressed that we continued learning so smoothly. It strengthened their trust in the school." Teacher Iman stated, "We felt more professional and capable this time. That changed how I see myself as a teacher." Still, a few teachers emphasized that usefulness was conditional on experience and prior investment. Teacher Nour said, "Without what we learned during the pandemic, this would have been a disaster. It's the same tools, but we're better users now."

(2) Perceived Ease of Use. In contrast to the pandemic experience, most teachers found the technological aspect of online learning during the war manageable. Teacher Samar explained, "I already knew the tools, so I focused on teaching, not figuring out how Zoom works." Teacher Lina added, "Everything was smoother. We didn't waste time on technical problems like before." Digital literacy had clearly improved for both teachers and students. Teacher Asma commented, "Even students who struggled last time knew what to do. The learning curve was gone." Teacher Dana reflected, "I didn't have to explain everything again. They were independent. That saved me energy."

Some challenges remained, particularly around emotional and social engagement. Teacher Walaa said, "It was easier technically, but emotionally harder. The war was scary. Sometimes I couldn't get students to focus." Teacher Hadel added, "There were days when the tension made teaching feel mechanical. But the platform helped us stay connected."

Still, teachers were more confident in managing their classes online. Teacher Aseel shared, "I created routines. Students knew what to expect, and that gave them stability." Teacher Siham said, "It wasn't ideal, but it was workable, and that's a big improvement from COVID." The infrastructure was also stronger. Teacher Fatima noted, "This time, the school had backup plans. We had guidelines and tech support."

(3) Intention to Integrate Digital Tools in Future Teaching. The experience of teaching during war positively influenced many teachers' intentions to integrate digital tools into future classroom practices. Teacher Roz said, "Now I see technology as part of my toolbox. It's not either/or; it's both." Teacher Lina added, "I already use online platforms for assignments and feedback. I plan to keep doing that."

Several teachers described a shift in mindset, from viewing digital tools as a temporary solution to seeing them as a long-term asset. Teacher Dana said, “It’s not just about emergencies. I realized tech helps with everyday teaching too.” Some teachers said digital tools increased their instructional flexibility. Teacher Iman reflected, “I recorded short videos and used them even after we returned to school. Students love having material to review.”

Others acknowledged ongoing limitations but expressed a desire to use technology selectively. Teacher Samar explained, “I’ll keep what worked, especially for homework and communication. But I won’t rely on it for everything.” A few teachers remained cautious, however. Teacher Fatima stated, “I prefer face-to-face teaching. I’ll use technology to support, not replace it.” Teacher Siham added, “Not all content works well online. We need to be thoughtful in how we use it.”

Overall, the wartime crisis solidified the role of digital tools as part of teachers‘ regular pedagogical repertoire. Teacher Hadel concluded, “We used to be afraid of technology. Now we see it as something we can control and use well.”

Cross-case Comparative Findings

Table 1 synthesizes the findings across the two cases.

Table 1

Comparison of the COVID-19 Pandemic and the Iron Shields Wartime Period Based on TAM

TAM Dimension	COVID-19 Pandemic (2020)	Wartime Period (2024)
Perceived Usefulness	Limited and inconsistent usefulness due to lack of preparation	High perceived usefulness supported by prior experience
Perceived Ease of Use	Low ease of use, many technical and emotional challenges	Improved ease of use, fewer technical barriers, better digital fluency
Intention to Integrate	Divided attitudes, dependent on personal experience and training	Broad willingness to integrate tools in future teaching

Over time, there was a growth in both positive perceptions and practice. During the COVID-19 pandemic, the transition to online learning was abrupt and unstructured, leading to mixed experiences. Teachers struggled with unfamiliar platforms, unequal access to devices, and a lack of pedagogical models. Although many acknowledged the potential of digital tools, their perceived usefulness was often overshadowed by logistical and emotional barriers. In the wartime context, teachers entered remote learning with prior experience, increased confidence, and refined digital strategies. Their perceptions of usefulness and ease

of use were more stable and positive. Importantly, their willingness to integrate digital tools in future teaching was significantly higher, with many viewing technology as a permanent enhancement of their pedagogy. Findings suggest familiarity, support, and accumulated experience are key enablers of technology acceptance. Teachers' attitudes evolved from initial compliance in 2020 to confident and proactive integration in 2024. This evolution reinforces the core assertion of TAM: acceptance is not only about the tool's features, but also about the context, competence, and confidence surrounding its use.

Discussion

This study explored Arab-Israeli teachers' perceptions of online learning in two crisis contexts, the COVID-19 pandemic and the Iron Shields War, using TAM as an analytical framework to understand how attitudes towards digital tools evolved. Findings showed a clear progression, reflecting a shift from forced adoption under pressure to confident and intentional integration of technology. Importantly, this progression cannot be explained by technological exposure alone; rather, it reflects a cumulative process shaped by contextual, cultural, and institutional conditions that reconfigured teachers' professional agency over time.

Perceived Usefulness

During the pandemic, many teachers identified the potential of digital tools to enhance instructional practices, increase student engagement, and develop 21st-century skills (Rafiq et al., 2024; Vasel, 2023). However, this perceived usefulness was tempered by limited preparedness, lack of pedagogical models, and the emotional strain of crisis-driven adaptation (Panadero et al., 2022). As reflected in the cross-case comparison, teachers' assessments of usefulness during this period were often tentative and situational, shaped by the immediate demands of emergency remote teaching rather than by established pedagogical experience.

Teachers had a more consistent and confident perception of the benefits of digital platforms during the wartime crisis. Drawing on prior experience, they were able to implement tools more effectively, personalize instruction, and use technology to maintain a sense of continuity and emotional stability for students, a finding echoed in research conducted in wartime educational contexts elsewhere (Ovcharuk, 2023; Sytnykova et al., 2023). In contrast to the pandemic period, perceived usefulness was grounded in familiarity; teachers relied on previously developed digital routines, not improvised solutions.

The evolution underscores a key principle in TAM: perceived usefulness increases not only with exposure to the technology itself, but also with accumulated experience and successful application. The cross-case comparison indicates that the pandemic functioned as an initial point of exposure to online teaching, while the wartime context enabled a consolidation of digital practices, contributing to more stable and confident perceptions of pedagogical value. Previous research has similarly shown digital tools are more likely to be seen as useful when integrated within a familiar pedagogical framework (Abdulrahaman et al., 2020; Bray & Tangney, 2016; Shamir et al., 2017). Building on this literature, the present findings suggest that differences in perceived usefulness across the two crises were primarily related to changes in teachers' accumulated experience and preparedness, rather than to the technological tools themselves.

Perceived Ease of Use

The contrast between the two periods was stark for perceived ease of use. During the pandemic, teachers experienced significant difficulties navigating new platforms, managing technical breakdowns, and addressing the digital divide among students. Many expressed frustration with the need to teach and troubleshoot simultaneously, often without adequate training or support (Norman et al., 2022). In this initial crisis period, ease of use was frequently described as limited and burdensome, constraining teachers' ability to focus on instructional decision-making.

By the time the war broke out, however, the majority of teachers had become more digitally literate. They reported smoother implementation, greater familiarity with tools, and a stronger infrastructure within their schools. The students themselves had gained experience, reducing the overall technological burden. While emotional stress persisted due to the wartime context, the technical and instructional processes were described as far more manageable (Lytvyn et al., 2024; Sytnykova et al., 2023). In contrast to the pandemic period, teachers saw online teaching as technically manageable, allowing more attention to pedagogy and less to technological problem-solving.

It is important to situate these findings within the access conditions under which online learning took place during each crisis period. During both the pandemic and the war, instruction combined synchronous Zoom-based teaching with asynchronous self-directed learning, and learning occurred primarily in students' homes rather than school facilities. Internet access and connectivity were generally more stable during the pandemic. The wartime period was characterized by more frequent disruptions; some students participated from shelters, and this occasionally affected signal quality and continuity of connection. These contextual conditions help explain why, despite overall improvement in perceived ease of use due to accumulated experience, infrastructural constraints remained a limiting factor in the second crisis.

Previous work has found that continuous exposure, hands-on practice, and professional development are crucial for overcoming initial barriers (Francom, 2020; Kopcha, 2012). The findings affirm TAM's emphasis on the role of perceived ease of use in shaping technology acceptance. They add to the literature by suggesting perceived ease of use is not static; it evolves with time and training. Viewed through a cross-case lens, the findings indicate the perceived ease of use shifted gradually across the two crises, in parallel with teachers' growing familiarity with online teaching practices.

Intention to Integrate Digital Tools in Future Teaching

Teachers' willingness to continue using digital tools post-crisis differed markedly for the two periods. During the pandemic, intentions were fragmented: some educators embraced the flexibility and innovation made possible by digital platforms, but others remained skeptical, citing fatigue, disengagement, and pedagogical goals (Bajaj et al., 2021; Herawati et al., 2022). These fragmented intentions reflect the emergency-driven nature of technology use during the pandemic; adoption was situational and shaped by immediate constraints, not by sustained pedagogical planning. Teachers reflecting on the wartime period expressed clear and confident intentions to integrate digital tools into their future classroom practices. They viewed technology not as a temporary solution, but as a lasting enhancement that could support differentiated instruction, formative assessment, and student autonomy. Their intentions were articulated with greater clarity and selectivity, drawing on prior experience with online teaching and a clearer understanding of which tools were pedagogically valuable.

This shift aligns with recent literature suggesting behavioral intention increases when both perceived usefulness and ease of use are present (Venkatesh & Davis, 2000). From a cross-case perspective, the findings suggest that strengthened perceptions of usefulness and ease of use contributed to more stable and coherent intentions to integrate digital tools. The wartime experience, building on lessons from the pandemic, created a stronger foundation for intentional and strategic adoption. Teachers moved from reactive to proactive use of technology—a key indicator of meaningful integration. Rather than reflecting a simple continuation of emergency practices, this transition indicates a shift toward more deliberate consideration of technology as part of teachers' regular instructional repertoire. Moreover, changes in intention were not only individual but also institutional. Teachers said school leadership, infrastructure, and professional cultures were more supportive in 2023–2024, reinforcing their motivation to continue using digital tools.

Together, these cross-case findings suggest that teachers' intentions evolved over time in parallel with their accumulated experience and growing confidence in using digital tools under crisis conditions.

Interaction of TAM Dimensions Across Successive Crisis Contexts

Findings for the two crisis periods indicate that perceived usefulness, perceived ease of use, and intention to integrate digital tools were not experienced as independent dimensions but as interrelated perceptions that evolved together. During the COVID-19 pandemic, difficulties related to ease of use often limited how usefulness was evaluated, contributing to unstable intentions regarding future integration. In contrast, during the wartime period, accumulated experience enabled greater ease of use, supporting more consistent perceptions of usefulness and clearer intentions to integrate digital tools.

Situated within the Arab-Israeli educational context, this interaction reflects how technology acceptance developed under conditions of limited preparedness and structural constraint, and how repeated crisis exposure enabled a gradual re-alignment of these perceptions. TAM thus serves to interpret not isolated attitudes but the evolving relationships among perceptions across successive emergency contexts.

Limitations and Future Research

A limitation of this study was its reliance on teachers' self-reported perceptions, which reflect subjective experiences rather than direct classroom observations or student learning outcomes. Accordingly, the findings are based on teachers' self-reported interpretations of their online teaching experiences, not on objective measures of instructional quality or learning outcomes. Another limitation was the study design; data were collected at the end of each crisis period with two different groups of teachers, enabling comparison of collective patterns rather than individual longitudinal change. The participant groups were unbalanced in size (23 vs. 18), and the second group consisted exclusively of female teachers, limiting cross-period comparability. Finally, the relatively small sample size and the context-specific focus on Arab teachers in Israel may limit the generalizability of the findings to other educational systems or crisis settings.

Future research could complement the present findings with longitudinal or mixed-methods studies that incorporate classroom observations or performance data to capture how teachers' evolving technology acceptance translates into measurable

instructional impact. Studies should also explore students' and school administrators' perspectives on online teaching during a crisis.

Conclusion

The findings suggest a process of maturation in teachers' engagement with educational technology. The COVID-19 pandemic served as an abrupt initiation into digital teaching, marked by struggle and improvisation. During the wartime period, increased experience, infrastructure, and confidence converged to produce more sustainable and positive perceptions.

The study contributes to the online learning literature by showing that teachers' engagement with online teaching is shaped cumulatively rather than episodically. Rather than responding to each emergency in isolation, in the second crisis, teachers drew on prior experience to re-evaluate the usefulness, ease of use, and future integration of online teaching practices. Importantly, these shifts were not driven by technological familiarity alone, but by differences in the nature of the crisis contexts, including levels of institutional preparedness, stability of learning conditions, and the emotional and structural demands on teachers and students.

The study underscores the dynamic nature of technology acceptance and highlights the importance of longitudinal support—pedagogical, technical, and emotional—for fostering deep and lasting integration of digital tools in educational contexts. From a practical perspective, the findings point to the need for sustained, experience-based professional development that moves beyond emergency training toward pedagogically grounded integration of digital tools. At the policy level, investment in continuous teacher training, school-level technological infrastructure, and clear guidelines for online teaching in crisis situations may strengthen system readiness and support more effective and resilient online learning practices.

Availability of Data

The dataset used in this study is accessible upon reasonable request, subject to the author‘s approval.

Declaration of Competing Interest

The author declares no competing interests.

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Appendix A

Interview Questions and Their Analytical Alignment with the Research Questions and the TAM Framework

Table A1

Alignment Between Research Questions, TAM Dimensions, and Interview Questions

Research Question	TAM Dimension Guiding Analytical Interpretation	Interview Questions (examples)
RQ1	Perceived usefulness	How did each crisis period influence your perception of the effectiveness of online teaching compared to traditional methods?
RQ1	Perceived usefulness	What factors motivated you to adopt technological tools in each context, and why were they significant?
RQ1	Perceived usefulness	While we acknowledge the benefits of technology in education, did you experience any drawbacks during either crisis period? If so, what were they?
RQ1	Perceived ease of use	What specific challenges did you encounter during each transition to remote learning?
RQ1	Perceived ease of use	Do you feel adequately skilled in using technological tools to effectively teach your students, and did this change between the two crises?
RQ2	Intention to integrate digital tools	What is your stance on the integration of technology in your teaching practices during each of the two periods?
RQ2	Intention to integrate digital tools	In your opinion, are schools better prepared today for the integration of technology, given their experiences during both the pandemic and the wartime period?
RQ2	Intention to integrate digital tools	Do you believe that your school environment fosters an atmosphere that encourages teachers to adopt technology in times of crisis and beyond?

Beyond the Screen: Students' Voices on Synchronous Online Learning in Higher Education

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Abstract
This study explores students' perceptions of synchronous learning during a period of rapid pedagogical transformation in higher education. Triggered by a systemic shift from traditional face-to-face instruction to online formats, institutions were compelled to redesign their teaching methods, communication channels, and assessment practices. Drawing on qualitative data from 5,154 open-ended responses in Student Evaluations of Teaching (SET) across two Israeli colleges, the research investigates how students experienced and interpreted these abrupt instructional changes. Four overarching themes emerged from the analysis: (1) the development and importance of soft skills, (2) the role of course structure, (3) perceptions of instructional professionalism, and (4) the influence of the digital platform. These findings offer insights into students' adaptive responses to institutional change and contribute to the understanding of synchronous online learning as a complex pedagogical process.

Keywords: Online learning**,** Student Evaluations of Teaching (SET)**,** performance, higher education

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Periods of crisis and disruption often accelerate existing trends in education, prompting rapid transitions from conventional in-person instruction to remote learning modalities. In recent years, many higher education systems faced such a shift, most notably during the COVID-19 pandemic, which acted as a catalyst for large-scale digital adaptation (Mathieu et al., 2020; Owusu-Fordjour et al., 2020; Powell et al., 2022). These transitions reshaped students' academic experiences and daily routines, introduced new modes of teaching and assessment, and redefined communication with faculty and administrative staff (Bezerra, 2020; Gonzalez et al., 2020; Kamarianos et al., 2020).

Platforms such as Zoom have become commonplace tools for conducting assessments, facilitating discussions, and giving lectures. Both teachers and students faced many difficulties because of this abrupt change, which necessitated adjusting to new pedagogical strategies, technologies, and interaction styles (Stefanile, 2020). The primary mode of academic engagement shifted to virtual platforms, which significantly changed the learning experience for students and highlighted the pressing need to comprehend the subtleties of effective online teaching in this newly prevalent modality (Turnbull et al., 2021).

This study explores students' perceptions of synchronous learning using Student Evaluations of Teaching (SET), focusing on the open-ended parts of the evaluations, where students evaluate the course and the instruction in their own language (without targeted questions). This feedback, provided by students, reveals what the students believed to be the key elements of effective synchronous teaching for themselves.

Thus far, there is no qualitative research that has yet been conducted on students' responses to studying via Zoom during the COVID-19 pandemic. Much of the existing research on student feedback (e.g., Almahasees et al., 2021; Cranfield et al., 2021; Powell et al., 2022) relies on quantitative data (e.g., surveys with rating scales). Qualitative studies that delve deeply into the reasons behind student ratings and the specific language they use to describe their experiences in online settings are less prevalent. The current study examines students' perceptions of specific courses in which they participated, enriching the literature with nuanced and sensitive observations described in their own words. This qualitative approach can provide richer and more refined insights into the underlying values and priorities regarding different aspects of online teaching.

Online learning had become an accessible alternative to on-campus studies, especially during crises when academic institutions are closed (such as wars and natural disasters), and, of course, after the COVID-19 crisis (Asirvatham & Jamil, 2025). Therefore, it is important to deeply understand the finer distinctions that students raise about what helps them learn effectively. Since online learning has nowadays become a significant and often the primary mode of delivery in higher education, comprehending what students value in this environment is essential for educators and institutions to design effective and engaging online courses. This research directly taps into the student voice, providing valuable insights into their experiences and priorities. Based on these observations, our research question is:

> What dimensions of synchronous online teaching do students emphasize in their open-ended SET narratives, and how do these dimensions illuminate the relational, structural, professional, and technological components of their learning experience?

Definition of Key Terms and Scope Boundaries

To clarify the conceptual scope of this study, several key terms require definition. "Online learning" is used in the literature as an umbrella term referring to instruction delivered through digital platforms, encompassing synchronous, asynchronous, and hybrid formats. The present study, however, focuses specifically on "Synchronous online learning," defined as real-time, instructor-led instruction conducted through videoconferencing technology.

More precisely, the data analyzed here derive from courses delivered via Zoom-based synchronous instruction during the 2020–2021 academic year, a period marked by rapid pandemic-driven transitions to remote teaching. Accordingly, the findings reflect students' experiences within this specific technological and temporal context.

The term "student perceptions" refers to students' subjective evaluations, interpretations, and meaning-making processes as articulated in the open-ended sections of the Student Evaluation of Teaching (SET) instrument. These narratives capture how students describe and prioritize dimensions of their learning experience rather than objective measures of instructional effectiveness.

This clarification delineates the scope of the study and indicates that the findings are most directly transferable to synchronous online teaching environments, particularly those relying on videoconferencing platforms.

Review of Related Literature

Challenges in the Transition to Online Learning: A Theoretical Framework

The rationale for this study is based on four theories concerning the challenges created by the transition to online learning. First, this research relies on Moore's (2013) Transactional Distance Theory, that maintains that teacher-student separation (as, for example, distance learning on Zoom) is more pedagogical and psychological than merely geographical. Moore's theory indicates that the greater transactional distance, the greater the detrimental impact on learning outcomes (Elyakim et al., 2017).

Moore (2013) identified three interaction domains that exist in distance learning: learner-content interaction, learner-instructor interaction, and learner-learner interaction. Later on, a fourth domain of interaction—learner-interface interaction—was introduced and advanced Moore's theory by considering the interactions that take place between students and technology in the telecommunications era (Chen, 2001). According to the theory, effective online teaching strategies, such as clear communication, well-structured course design, and responsive support, can compensate for the barriers to effective learning that arise from the "distance" created by distant learning between lecturers and students (Kozlova, 2022).

Second, this research relies on the concept of Social Presence Theory (Lowenthal, 2010; Short et al., 1976) which investigates how digital interfaces affect the "sense of being with another" in communication based on technology (Biocca et al., 2003). The theory suggests that the feeling of being "there" and connected with others in a virtual environment significantly impacts learning outcomes and satisfaction. In online courses, instructor presence, characterized by timely and personalized communication, active participation in discussions, and the creation of a welcoming atmosphere, can mitigate feelings of isolation and enhance engagement (Lowenthal, 2010; Wut & Xu, 2021).

Third, this study is grounded in the Technology Acceptance Model (TAM) (Davis, 1989). According to this theory, students' acceptance of Zoom as a primary learning platform relied on its perceived usefulness for academic success and its ease of use. Initial doubts about online learning likely stemmed from concerns over its ability to replicate in-person engagement, while perceptions were also shaped by students' technical skills, internet access, and familiarity with Zoom's features (Alfadda & Mahdi, 2021; Wedari et al., 2022). Computer self-efficacy (Achim & Al Kassim, 2015) influences students' perceptions of Zoom's usefulness and ease of use, which in turn shape their attitudes, intentions, and actual usage (Mohamed Riyath et al., 2022). Zoom's popularity is largely attributed to its user-friendliness and technological reliability, though technical issues, such as unstable internet, delays, and device limitations, can negatively affect student satisfaction (Aristovnik et al., 2020).

Finally, the transition to online learning could be examined through Self-Determination Theory (SDT) (Ryan & Deci, 2017). The transition to online learning highlights key psychological needs—autonomy, competence, and relatedness—that shape students' virtual learning experiences (Ryan & Deci, 2017; Wang et al., 2019). While online education can support autonomy and competence, it often challenges the need for relatedness due to reduced interpersonal interaction (Jeon & Lee, 2023; Salikhova et al., 2021). Use of interactive tools like polls and breakout rooms enhances engagement and satisfaction, whereas monotonous, non-interactive classes may lead to alienation (Lowenthal et al., 2020). As indicated, timely feedback and personalized support also play a vital role in student satisfaction and relatedness (Hodges et al., 2020).

Empirical Research on Students' Perceptions of Online and Synchronous Learning

A growing body of empirical research has examined students' perceptions of online learning environments. Quantitative studies consistently find that students value instructor presence, clarity of communication, timely feedback, and course organization as key predictors of satisfaction in online courses (e.g., Ismaili, 2021; Cranfield et al., 2021). In synchronous formats specifically, real-time interaction, opportunities for participation, and perceived instructor responsiveness have been identified as central contributors to engagement and perceived learning (Lowenthal et al., 2020).

Research conducted during the COVID-19 pandemic further highlights the importance of relational factors in synchronous online environments. Studies report that students frequently emphasize instructor empathy, adaptability, and communication style as critical determinants of their experience (Means & Neisler, 2021). At the same time, technological reliability and course structure were found to influence students' sense of stability and learning effectiveness during emergency remote teaching (Hodges et al., 2020).

Within SET research specifically, empirical studies often rely on structured Likert-scale measures that capture predefined dimensions such as clarity, organization, and instructor effectiveness. However, fewer studies have examined open-ended narrative responses to identify how students themselves frame and prioritize dimensions of online instruction. As a result, much of what is known about student perceptions in synchronous online contexts derives from survey-based instruments rather than large-scale qualitative analysis of student-generated narratives.

Lecturers' Evaluations as Tools for Identifying Student Needs

Student evaluations of teaching (SETs) are a ubiquitous element of the academic landscape, serving as a primary mechanism for gathering student feedback on instructor performance and course quality (Hammonds et al., 2017). Traditionally, these evaluations

have been utilized for a variety of purposes, including promotion and tenure decisions, formative feedback to instructors for pedagogical improvement, and overall program evaluation (Harrison et al., 2022; Ulker, 2021). While the focus has often been on assessing instructor effectiveness in face-to-face settings, SET's rich textual data within open-ended responses can offer a valuable, albeit sometimes underutilized, window into the student experience. These qualitative comments can reveal underlying student needs, preferences, and perceptions regarding various aspects of the learning environment, going beyond the quantitative ratings to provide nuanced insights into what resonates with students and where challenges exist (Harrison et al., 2022; Mok et al., 2021).

Student comments in SETs became especially significant considering the pandemic-induced shift to online learning. These assessments serve as a direct conduit for student voices, expressing their successes, struggles, and experiences in the online learning environment (Warfvinge et al., 2022). Researchers learn more about what students believe to be successful online teaching strategies by closely examining the language, themes, and sentiments conveyed in these qualitative responses. For example, recurring remarks regarding the usefulness of interactive tools, the clarity of online instructions, the sense of community that is created (or not) in the virtual setting, and the availability of resources, all draw attention to valuable components of effective online pedagogy (Boysen, 2023; Warfvinge et al., 2022). Thus, the qualitative data can inform pedagogical changes and the creation of more successful online learning experiences, ultimately promoting a more student-centered approach in the changing higher education landscape (Boysen, 2023).

Research Gap and Contribution

Despite extensive theoretical development and growing empirical research on online learning, several gaps remain. First, while prior studies identify factors such as engagement, instructor presence, and technological functionality, these dimensions are typically measured using predefined survey constructs rather than emerging inductively from students' own language (e.g., Cranfield et al., 2021; Means & Neisler, 2021). Second, few studies have systematically analyzed large-scale open-ended SET responses to examine how students narratively construct their experiences of synchronous online instruction (Sun & Yan, 2023; Ullmann & Rienties, 2021). Third, the rapid transition to Zoom-based learning during 2020–2021 provides a unique context in which students experienced fully synchronous remote instruction, yet qualitative syntheses of these experiences remain limited (Almahasees et al., 2021; Powell et al., 2022).

The present study addresses these gaps by conducting a thematic analysis of open-ended SET responses to identify the dimensions of synchronous Zoom-based instruction that students themselves emphasize. By grounding the analysis in students' narratives, this study contributes an empirically derived framework that complements existing survey-based findings and refines theoretical models of online learning. Therefore, as mentioned in the introduction, our research questions is: What dimensions of synchronous online teaching do students emphasize in their open-ended SET narratives, and how do these dimensions illuminate the relational, structural, professional, and technological components of their learning experience?

Method

Qualitative Research Methodology

This study adopts a qualitative-constructivist paradigm (Creswell, 2014; Taylor et al., 2016) to examine students' perceptions of synchronous online learning. Given the exploratory nature of the research questions and the large corpus of open-ended Student Evaluations of Teaching (SET) responses, inductive thematic analysis was selected as the most appropriate analytic approach (Braun & Clarke, 2017). This approach allows patterns and meanings to emerge from participants' narratives while preserving contextual nuance and interpretive depth.

Procedure

Open-ended SET responses were collected from two Israeli higher education institutions (one public and one private) during the 2020–2021 academic years, when instruction was conducted synchronously via Zoom. Institutions were recruited through convenience sampling by contacting Directors of Teaching and Learning. Both institutions granted permission to use anonymized SET files following Institutional Review Board (IRB) approval. It was important to discern if there were different expectations or demands from students at a public versus private institution, in line with consumerism theory (Eagle & Brennan, 2007; Guilbault, 2018) but no such differences were evident.

The dataset included only open-ended student comments related to online instruction. No identifying information about students or lecturers was included in the files provided to the research team. All responses were originally written in Hebrew. The thematic analysis was conducted using the original Hebrew dataset to preserve semantic nuance and contextual meaning. For publication purposes, illustrative excerpts were translated into English by the first author, who is fluent in both languages. A bilingual academic colleague independently reviewed a sample of translated excerpts to ensure semantic equivalence. Minor refinements were made where necessary to preserve tone and intent.

Participants

The dataset comprised 5,154 anonymous open-ended responses (1,219 from the private institution and 3,935 from the public institution). Responses were drawn from undergraduate and graduate programs in education, law, business administration, and behavioral sciences. Most comments related to regular academic courses, with a smaller portion referring to seminars, workshops, and practicum-based instruction. Completion of SETs was voluntary. Students were not required to complete evaluations, and multiple responses from the same student were possible if they were enrolled in multiple courses.

Data Analysis

The data were analyzed using inductive thematic analysis following Braun and Clarke's (2017) six-phase framework. All 5,154 open-ended responses were exported into structured spreadsheets and coded manually.

Phase 1: Familiarization. Two authors immersed themselves in the dataset through repeated reading of the responses to gain a comprehensive understanding of recurring meanings, patterns, and linguistic nuances.

Phase 2: Generating Initial Codes. The first author conducted open coding across the dataset, identifying meaningful segments of text and assigning preliminary codes. To enhance analytic rigor, the second author independently coded a subset of responses to assess interpretive consistency. Coding consistency was periodically

reviewed collaboratively across the full dataset. Discrepancies were discussed until consensus was reached, leading to refinement of code definitions and development of a shared coding framework.

Phase 3: Searching for Themes. Related codes were examined for conceptual similarity and grouped into 18 preliminary themes reflecting key aspects of students' experiences of synchronous online learning.

Phase 4: Reviewing Themes. The 18 themes were collaboratively evaluated for coherence, overlap, and distinctiveness. Alternative thematic structures were considered and discussed before agreement was reached on the most conceptually parsimonious organization.

Phase 5: Defining and Naming Themes. The themes were conceptually clustered into four overarching categories and corresponding sub-themes based on internal consistency and recurring language patterns. Although this stage involved interpretive abstraction, it was not structured according to predefined theoretical models. The clustering process followed a collaborative interpretive procedure based on conceptual similarity, internal coherence, and recurring linguistic patterns rather than theoretical alignment.

Phase 6: Producing the Report. After finalizing the thematic structure, the full dataset was revisited to ensure consistent application of themes. Representative excerpts were selected to illustrate each theme, and frequencies and percentages were calculated to indicate relative prevalence.

Although the literature review presents four theoretical frameworks relevant to online learning, these did not guide the coding process. The analysis remained inductive and grounded in the data. The theoretical frameworks functioned as sensitizing concepts during interpretation and were explicitly integrated in the Discussion section to contextualize and extend the empirical findings.

Importantly, the four overarching themes (soft skills, structuredness, professionalism, and technological medium) emerged from the clustering of data-driven themes and were not constructed to correspond directly to the four theoretical frameworks presented in the literature review. The clustering process was guided by conceptual coherence within the dataset rather than by alignment with specific theories. The theoretical frameworks (transactional distance, social presence, TAM, and SDT) were subsequently used in the Discussion section as interpretive lenses to contextualize and extend the empirical findings. Any conceptual overlap between themes and theories reflects interpretive resonance rather than deductive structuring.

Results

The review included a thorough theme analysis that emerged from the students' SETs. The results of this theme analysis were divided into four categories: (1) soft skills, (2) structuredness, (3) professionalism, and (4) the technological medium, with soft skills capturing relational dimensions and professionalism reflecting instructional expertise and academic conduct. The most prevalent sub-themes were care (n=1561; 30.3%) and clarity (n=1329; 25.8%), reflecting students' strong emphasis on relational and structural aspects of synchronous online learning. Although certain relational descriptors appear across multiple themes, each category captures a distinct functional dimension of students' experiences. The themes are presented in Table 1.

Table 1

The themes of the students

Theme	Sub-theme	
1.Soft skills	1.1 Supportive behaviors	1.1.1 Availability (n=248) 1.1.2 Care (n=1,561) 1.1.3 Responsiveness (n=371)
	1.2 Self-Management	1.2.1 Patience (n=434) 1.2.2 Pace (n=531) 1.2.3 Adaptiveness (n=329) 1.2.4 Trustworthiness (n=438)
2. Structuredness	2.1 Synchronization (n=476) 2.2 organization (n=350) 2.3 The course's presentations (n=295)	
3. Professionalism	3.1 Content professional (n=270)	
	3.2 Pedagogical professional	3.2.1 Thought provoking (n=1,519) 3.2.2 Clarity (n=1,329) 3.2.3 Engagement (n=426)
4. The technological medium	4.1 Zoom Fatigue	4.1.1 Difficulties with concentration (n=101) 4.1.2 Straightforwardness (n=223)
	4.2 Technical problems (n=164) 4.3 Privacy (n=50)	

Soft Skills

Many of the students addressed various soft skills necessary for learning via Zoom.

Supportive Behaviors

Supportive behaviors of a lecturer towards students are actions and approaches aimed at creating a positive and encouraging learning environment.

Availability. Numerous students addressed the fact that the lecturer was available for them after the lesson for questions or problems they have. Of course, in some cases they referred to their frustration due to the instructor's lack of availability. This irritation could be attributed to the fact that after the lesson, students who are uncomfortable asking questions in a big group might feel more at ease addressing a lecturer privately. Here are several samples of the students' responses:

> *Response 736*: The best lecturer I had in my degree, completed lessons for those who couldn't make it to the original lesson, at the expense of his time and when it was convenient for us.

Response 1524: In this course, as in the research methods course, the lecturer was incredibly available, answered questions and made sure that we understood everything.
Response 186: The availability of lecturer is very low. He asks to be contacted only by email and does not respond, only after 2-3 reminders.

Care. Many students took notice of the fact the lecturers put in much effort and were committed to the students' success. These responses were a function of the lecturers' enthusiasm or their genuine desire and concern that all their students would understand them and, consequently, succeed in the course. Examples include:

Response 3358: A teacher who inspires those who are going to become teachers themselves—empathetic, inclusive and attentive, and very caring towards the students.

Response 1040: He always makes us feel good and pleasant in class and always cares about our well-being and tries to help in every possible way, considers our requests and always finds the best way to assist us.

Response 629: The lecturer was God sent, and she knows how to teach and convey the material exactly as expected for a student who is just learning English. A very considerate lecturer and always alert to any problem of any student who is struggling. There is nothing left unclear at the end of her lesson.

Response 423: He cares about the students and relates the lesson to how theoretical material is reflected in our everyday life.

Responsiveness. Many students referred to the manner in which the lecturer answered their questions during class. Many responses related to the lecturers' attitudes towards the students as reflected in the way they answered their questions. Notably, however, in this sample, various students indicated that the lecturer should have better control of the classroom and left less time for questions that distract them from teaching. Examples of students' responses to teacher responsiveness include:

Response 93: Indifference in answering students' questions. The lecturer answers briefly without a detailed and clear explanation. Without outside help, I do not have the ability to pass this course.

Response 338: He cares about the students, always asks if the material is clear and answers questions in detail. It's fun to study with him.

Self-Management

These actions and approaches of lecturers are aimed at managing themselves and their responsibilities efficiently and professionally.

Patience. Many student responses stressed the importance of lecturers' patience with them; and, in some cases, they complained about their lecturers' lack of patience. Examples include:

Response 308: The lecturer was patient and did not finish a class before everyone understood the material being taught.

Response 410: …. Sometimes she loses patience and becomes less pleasant and does not allow the questions to be asked. This hurts the desire to listen to her and even leave the class!

Response 4455: In my opinion, there is a need for more listening and patience on the part of the lecturer. Beyond that, the content of the lesson should be delivered more slowly, and the lecturer should listen to the students' difficulties.

Pace. Several students addressed the pace of the lecturer, stressing that lecturers speak too quickly, such that it is difficult to keep up. Examples include:

Response 449: The material is interesting, unfortunately the lecturer teaches at his own fast pace; it's hard to follow him.

Response 476: As a student, it is very difficult for me to understand the material without the lecturer dictating to me because it is not my mother tongue and also because it is a new method for me. I had a lot of difficulty with this course. I repeated the recordings from the beginning to understand a little more.

Response 1626: The lecturer needs to slow down the pace of study a little. We felt that we studied to finish the material rather than to understand it.

Adaptiveness. Several students referred to learning in which lecturers adapted themselves to the medium of Zoom. In some cases, the lecturers were praised for understanding the challenges of studying in Zoom, while, in some cases the feeling was that lecturers did not adjust and simply continued to teach as they would have taught face-to-face without any consideration of the limitations of the situation. Here are some illustrations that demonstrate this point:

Response 625: She was one of the few lecturers who managed to adapt the lessons to Zoom in an interesting and simple way. She made sure to take a break every 45 minutes because she understands that after 45 minutes in front of a screen it's hard to concentrate. In addition, she made all kinds of questionnaires and distributed them to the breakout rooms to convey the message and create interest.

Response 481: An excellent form of study that adapts to our times and enables learning with pleasure.

Response 1686: An organized lecturer, adapted to distance learning, explains with the help of the computer board and in every possible way she finds so that everyone understands, and does not give up until everyone understands.

Trustworthiness. The students referred to various issues regarding the fairness of the lecturer. Some complained that lecturers utilized unfair and inconsiderate criteria; several suggested that the course required knowledge or skills they did not possess. Other comments included unfair treatment in grading papers or exams and even interpersonal dismissive or offensive remarks (even to the point of bullying). Sample responses include:

Response 870: The lecturer's sexist or sometimes ethnic remarks hurt students who come from a religious background or any background that is different in the landscape of the academy.

Response 1211: The attitude she gives to the students is sometimes terribly humiliating and irrelevant. It's not fun to attend class because it really insults us.

Response 4812: The lecturer acted unfairly in giving grades and giving rights to students with accommodations.

Together, these patterns indicate that students expected lecturers to combine interpersonal sensitivity with self-regulation to sustain engagement in Zoom-based environments.

Structuredness

The virtual environment could be chaotic, ambiguous, and disengaging. Therefore, many students emphasized their desire that the lecturer and the lesson will be clear, well-structured and organized.

Synchronization. This theme refers to the synchronization between the lesson, the written material, the chores, the practice, the syllabus, and the exams (mostly to synchronization between any two of these components). A synchronized course incorporates these various components that work in unison to produce a seamless educational experience. Student issues included discrepancies between the lecturer and lecturer assistant; inconsistencies between the syllabus and what was actually taught; and contradictions between what the lecturer taught and what appeared on the exam paper. Several students addressed the correct balance between practical and theoretical material. A selection of the students' responses is shown here:

Response 442: In my opinion, the material we studied didn't match the level of the assignments or the level of the test.

Response 1063: An unclear course. I feel that there is pressure because there is no complete understanding of what needs to be done in the assignments and there is no understanding of the entire lesson.

Response 794: The practice classes contributed a lot to understanding, and the assistant explains the material excellently and is more patient in these classes.

Organization. Some students reported that the course felt chaotic, that lessons were not well-organized, and that the lecturer changed the topic abruptly. Examples include:

Response 9: It would be more appropriate if the course was built gradually. There is a feeling of confusion, jumping from topic to topic, incomprehensible explanations (the lecturer probably assumes that all students have a background in programming).

Response 89: The lecturer conveyed the material in a very thought-provoking way, but nevertheless it is sometimes very difficult to follow the material because he constantly jumped from topic to another according to the students' questions and thus there is no continuous course of the lesson. The material was difficult to follow.

> *Response 4465*: The course is messy and unclear in all respects – the way of teaching, the form of the exam, the study material. There is no real answer to any question, we all left the course with the feeling that no one understands what we learned here.

Course Presentation. The students gave considerable weight to the course materials with an emphasis on the presentations and reference materials. They mentioned several issues: The appearance of the presentations (graphically), how they are organized, their ability to rely mostly on the visual presentations and not what the lecturer said verbally. Here are some illustrations of this theme:

> *Response 315*: The preparation for the classes is very impressive. It's amazing to see how much thought was put into how to conduct classes in the time of COVID-19. It is possible to listen to the lecturer in class without fearing that we will not have enough time to copy the text because at the end of the class all the material that was transferred is uploaded to the website.

> *Response 485*: Excellent lecturer listens to and answers all questions. The presentations are not good in my eyes, their colors (yellow, black and red), made it difficult for me to focus

> *Response 2610*: The presentations with the details are great, they provided a lot of explanations and knowledge about what is being studied.

This category, "structuredness," highlights students' emphasis on clarity, organization, and coherence in online courses. Students also valued well-organized lessons, as well as clear and visually accessible presentations that support independent study.

Professionalism

The students commented on the lecturers' professionalism, both in terms of their expertise in the subject matter and their pedagogical skills in teaching.

Professional Content. Several students stated their appreciation for the professionalism of the lecturer in the subject matter, and, in some cases, expressed how impressed they were by the instructors' expertise. For example:

> *Response 837*: A lovely person with an insane amount of knowledge of the material and I really appreciate him but I'm sorry to say that there is a big difference between knowledge and imparting knowledge. In addition to lecturing knowledge, you also need to know how to convey material and here, in my opinion, he falls and we are the ones who end up losing from this.

> *Response 220*: It is important for me to say that he is an excellent professional lecturer, there wasn't a question that he did not know how to answer throughout the course.

Professional Pedagogics

Thought Provoking. Few students took notice of how much the course was thought provoking, challenging, or intellectually stimulating. Thought-provoking elements encourage students to consider why and how, going beyond simple memorization. This may entail dissecting case studies, investigating various viewpoints, or using the found knowledge to address practical issues. Based on these observations, the deeper understanding allows for

more effective retention of the material and a stronger basis for subsequent learning. Several examples that illustrate this point:

> *Response 132*: Beyond being a lecturer who only shares and contributes his knowledge to the student, he gives a desire to learn and deepen our understanding. I wish the academy had more lecturers like him.

> *Response 358*: The most interesting lesson by far. Immersive lecturer, insanely interesting topics. The lecturer always wants us to open our minds and renew. I enjoyed every moment; it's a shame it's over.

> *Response 3631*: The lecturer can facilitate dialogue with and between the students. The material is very interesting and arouses curiosity and excitement and it is important to allow discourse.

Clarity. Lecturers' clarity was one of the most prominent themes in the student feedback. The students praised the lecturers whom they considered to be clear and well understood. Conversely, if the lecturers were not clear enough, this inadequacy was reflected in the general tone of the feedback. Below, several responses illustrate this theme:

> *Response 1121*: Most of the time in the course the information is conveyed in an understandable way, but sometimes it is difficult to understand the lecturer's wording, and this can cause confusion.

> *Response 624*: Clear and precise explanation helped me forget all the math anxieties from high school.

> *Response 4466:* The lecturer should have tried to illustrate the lessons more clearly because it is abstract and ambiguous material.

Engagement. Several students indicated that the course was conducted in an engaging manner that promoted a dynamic learning process and deeper comprehension. They stated that the lecturer used enjoyable and interesting methods to deliver the material such as exercises, guest lectures, unconventional teaching methods, games, and polls. Also, the lecturer demonstrated the applied value that results from theoretical learning, i.e. how much the course has real-life applications, thereby creating student engagement in learning. Examples include:

> *Response 3320*: The personal stories were a very interesting way to learn the different theories. I feel that through personal experience I was able to connect more and understand the material studied in a better way.

> *Response 163*: The lecturer is very nice but conveys the material in a very monotonous and boring way. It was impossible to listen to her.

> *Response 225*: The course was delivered in a reasonable manner but I'm sorry the lecturer doesn't deliver in an interesting way and seems to only be in a hurry to go through slides and talk non-stop at a record pace. That's not what I came to the academy for. Disappointing lecturer.

In the "Professionalism" category, students emphasized both content expertise and teaching skills. They appreciated lecturers with deep subject knowledge but stressed that effective delivery is equally crucial. Pedagogical professionalism was reflected in three areas: thought-provoking content, clarity of instruction, and engaging, interactive teaching methods.

The Technological Medium

Although all the themes revolved around teaching online, some of the student feedback was addressed specifically to the technological medium and its ramifications for learning.

Zoom Fatigue

Difficulties with concentration. Many students mentioned the difficulty of concentrating for long periods of time on Zoom, a phenomena recognized as Zoom fatigue. Compared to a classroom environment that is under control, the home environment is full of potential distractions. Here are some examples:

> *Response 908*: This is an important course that requires thinking and understanding, it would make more sense to put it at the beginning of the day rather than at the end. This is a course that is suitable to be taken during the hours when students are alert.

> *Response 875*: Excellent lecturer, delivery of the lesson in an excellent and fascinating way…. I feel that the bonus questions given during class make most students increase their concentration level. Among the few courses where my concentration level is at 100% from the beginning of the class to the end.

> *Response 423*: Delivers the lesson in a very interesting way, makes everyone listen and concentrate on the lesson.

Straightforwardness. This theme is very much related to the difficulty of concentrating in the classroom. Many students mentioned that the course in question was concise and "to the point."" Because students may find it difficult to stay focused in online learning environments for prolonged periods of time, short lectures with concise, well-organized material are simpler to follow and maintain students' interest throughout the Zoom session. Zoom lectures that go on for too long can make the students feel tired and less focused. Here are a few examples that illustrate this idea:

> *Response 535*: A concise, professional lecturer who sends summaries at the end of every lesson!!

> *Response 913*: An excellent lecturer who conveys the material in a matter of fact, quick and clear manner! I enjoyed it very much.

Technical problems. The Zoom media creates a variety of technological problems: connectivity issues, sharing content, lack of knowledge about operating the Zoom (lecturers and students alike), managing participants (e.g. muting participants) and hardware issues (cameras, microphone, speakers, etc.). The students commented on these issues and their effect on the learning experience. Examples include:

> *Response 4163*: The quality of the Internet broadcast must be improved; we encountered quite a few problems on the subject in all the courses.

> *Response 363*: The lecturer's microphone wasn't working well. I haven't understood what he's saying since the beginning of the semester. In the first practices it was impossible to understand his words. He changed the microphone, but it is still not working well.

> *Response 396*: The lecturer who knew best how to operate the Zoom learning system!

Privacy. Many students addressed the issue of opening the cameras on their computers during lessons. Some students stated that much time was spent on this allegedly trivial issue, but others stated that they consider it a question of privacy. Several students felt that a mandatory camera policy is unfair, especially as they feel more comfortable participating without the video. Here are some examples:

> *Response 682*: There wasn't a single lesson that ten minutes would not have been wasted on opening cameras. A very interesting course, but a lot of talk was about the cameras, which would also interrupt the lessons.

> *Response 1061*: It's not okay to require the opening of cameras!

> *Response 4783*: It's at least a little difficult for me in Zoom studies to have an open camera, which makes me uncomfortable.

Reflecting on the technological issues associated with distant learning, students reflected on how the online format shaped their learning experience. They raised concerns about Zoom fatigue, especially difficulty maintaining concentration during long sessions, and emphasized the value of short, focused, and well-structured lessons. Technical issues such as poor audio, connectivity, and platform navigation were common barriers. Additionally, privacy concerns arose regarding mandatory camera use, with some students expressing discomfort or frustration over enforced policies.

Discussion

This study contributes to understanding online learning through the lens of several theories. First, these findings are in line with the Transactional Distance Theory (Moore, 2013), which highlights the psychological and communicative gap between students and instructors. Unlike prior survey-based findings that emphasize dialogue and structure primarily through predefined quantitative indicators (e.g., Abuhassna & Alnawajha, 2023), our narrative data reveal how students interpret transactional distance as a relational and emotional experience shaped by care, pacing, and perceived attentiveness. Students' feedback underscores the need for clear communication, organized courses, and responsive teaching to reduce this distance. Lecturers who show patience, care, and adapt effectively to the online format help foster connection and engagement. In contrast, unclear instruction, fast pacing, and technical issues increase isolation and hinder learning. Clear, structured materials also play a key role in minimizing transactional distance (Moore, 2013). Prior empirical work on Transactional Distance Theory has consistently emphasized the central role of dialogue and structure in shaping student engagement and satisfaction, with nearly 90% of studies focusing on interaction and communication (Abuhassna, & Alnawajha, 2023). Our findings confirm this emphasis by showing that students' expectations in synchronous Zoom environments were strongly anchored in perceived instructor responsiveness and structural clarity, reinforcing the empirical link between dialogue, structure, and reduced transactional distance.

At the same time, our study extends prior research by demonstrating that in emergency-mediated synchronous contexts, transactional distance is experienced not only as a structural or communicative gap but as a relational and emotional phenomenon, suggesting that TDT may require a more explicitly human-centered interpretation in post-pandemic online learning environments.

The emphasis on soft skills and emotional expression highlights the continued relevance of Social Presence Theory in Zoom-based learning, underscoring the importance of instructors' responsiveness, care, and emotional engagement in fostering connection and reducing student isolation (Alsayer & Lowenthal, 2024; Lowenthal, 2010). Students valued lecturers who were responsive, caring, and engaged, qualities that enhance social presence and reduce feelings of isolation. In contrast, poor self-management, impatience, and lack of adaptation to online teaching signaled a low social presence, harming student experience. As Goleman (2000) noted, self-management is key to effective leadership. Creating a safe, supportive atmosphere is essential for meaningful interaction and positive learning outcomes in online settings (Kozlova, 2022). Prior empirical research on Social Presence Theory has consistently shown that higher perceived social presence is associated with greater student satisfaction and engagement in online learning (Weidlich et al., 2023). Our findings confirm this relationship, as students emphasized the importance of instructor visibility, responsiveness, and interpersonal warmth in synchronous Zoom environments

The SET feedback aligns closely with the Technology Acceptance Model (TAM), especially regarding perceived ease of use and usefulness (Bhatt & Shiva, 2020). Students emphasized the importance of organized, clearly delivered, and well-structured courses, reflecting their need for both content expertise and effective pedagogy. When online courses are synchronized and supported by clear communication and accessible materials, they reduce cognitive load and foster greater acceptance of the technology. Recent studies show that both educational and emotional support play a key role in promoting students' acceptance of digital learning—educational support enhances perceived usefulness, while emotional support improves perceived ease of use (Alshammari & Alkhwaldi, 2025; He et al., 2023). These findings highlight the need to combine clear instruction with emotional attentiveness to sustain engagement and reduce barriers to technology use.

The interpersonal aspects highlighted in the student feedback resonate profoundly with Self-Determination Theory–SDT (Ryan & Deci, 2017), emphasizing the critical role of relatedness, competence, and autonomy in the online learning experience. The consistent appreciation for lecturer patience, availability, responsiveness, effort, and fairness underscores the importance of fostering a sense of connection and belonging (relatedness). When lecturers demonstrate care, provide support, and create a safe environment for interaction, students' needs for relatedness are met, leading to greater engagement. Moreover, clear explanations, thoughtful responses to questions, and a lecturer's commitment to student success contribute to feelings of competence, empowering students in their learning (Jeon & Lee, 2023; Salikhova et al., 2021). Creating a supportive environment where students feel safe to ask questions promotes autonomy. Conversely, when such interpersonal support is lacking, students' motivation and satisfaction in online learning decline significantly. This paper's findings extend the SDT-based model presented in Shah et al. (2021) by shifting the focus from a structured "learning climate → need satisfaction → engagement" pathway to a more nuanced understanding of how students interpret online learning conditions. While that study found no direct effect of online learning climate on engagement, but a clear mediating role of need satisfaction/frustration, our paper deepens this by showing that students' lived

experiences (e.g., professionalism, soft skills, structure, technological mediation) shape how autonomy, competence, and relatedness are enacted in synchronous settings.

Taken together, the findings do not simply confirm the four theoretical frameworks but reveal subtle tensions among them. While Transactional Distance Theory and Social Presence Theory emphasize communication and relational closeness, the students' narratives suggest that structure and professionalism function not merely as supportive conditions but as emotional stabilizers in uncertain contexts. Similarly, although TAM focuses on perceived usefulness and ease of use, our data indicates that technological acceptance is inseparable from relational and pedagogical dynamics. These intersections suggest that existing models may insufficiently account for the affective and contextual layering of synchronous learning, pointing to a need for more integrative theorizing.

The emerging themes offer an empirically grounded framework that complements existing theories and deepens understanding of students' needs in online learning. Rooted in student perspectives, these research findings support the development of more nuanced, student-centered approaches for future research and practice. Beyond supporting existing frameworks, this study brings into sharper focus a critical and under-theorized element in online learning: *the need for personal connection and authenticity in the absence of full physical presence*. While previous literature has addressed the psychological and communicative dimensions of transactional distance (Moore, 2013) and the buffering role of social presence (Lowenthal, 2010), the current findings suggest that synchronous online platforms such as Zoom create a paradox: Students are simultaneously present and absent. They may log in yet feel invisible, attend yet remain disengaged. This liminal presence intensifies the need for *real relational intimacy*—for being *seen, known,* and *acknowledged*.

Student responses reflected a desire for more than just efficient knowledge transmission or technical fluency. They called for *human pedagogical presence*—a lecturer who not only teaches but listens, notices, and cares. This confirms Kozlova's (2022) and Hodges et al.'s (2020) claims about the relational deficit of emergency online teaching but goes further by grounding it in students' own words. What emerges is a need for *relational pedagogy*: emotionally intelligent, context-sensitive teaching that compensates for the medium's inherent impersonality (Goleman, 2000; Salikhova et al., 2021).

Furthermore, while the Technology Acceptance Model (Bhatt & Shiva, 2020; Davis, 1989) helps explain students' responses to interface and content design, it does not account for the *emotional cost* of disorganized, fast-paced, or indifferent teaching. This study extends TAM by showing how perceived ease of use and usefulness are filtered through a human lens: A course is "useful" if it is also humane, "easy to use" if the lecturer anticipates student challenges and mitigates them empathetically.

Lastly, the findings suggest that *students do not merely consume content online—they seek meaningful experiences.* The frequent mentions of unfair treatment, unstructured lessons, and alienating practices indicate that students view their online academic experience not just as a cognitive process but as a social and emotional journey. This aligns with Self-Determination Theory's emphasis on relatedness and autonomy (Ryan & Deci, 2017) but repositions it within the specific constraints and affordances of remote synchronous education. This study highlights that effective online synchronous learning depends not only on technology or instructional quality, but on restoring human connection. Students seek presence, attentiveness, and fairness—elements that foster engagement and trust. As AI automates content, the lecturer's added value lies in empathy, adaptability, and relational skills.

Unlike prior pandemic-era studies that primarily relied on survey-based measures of satisfaction and engagement, the present study offers a large-scale narrative analysis that foregrounds students' relational interpretations of synchronous learning**.** While a substantial body of pandemic-era research examined emergency remote teaching, much of it relied on survey-based designs focusing on satisfaction, engagement, or technology acceptance. In contrast, the present study draws on a large corpus of open-ended student narratives across two institutions to capture how learners articulated their expectations in their own words. By integrating Transactional Distance, Social Presence, TAM, and SDT within a single interpretive framework, the study moves beyond variable-based confirmation toward a relational and paradox-oriented understanding of synchronous online learning. In doing so, it contributes a qualitatively grounded, theory-integrative perspective that highlights tensions and contextual layering often underexamined in prior empirical work.

Practical Implications

These findings have broad practical implications for improving online teaching. Institutions should prioritize professional development that strengthens instructors' relational and communication skills in virtual settings. Course design must emphasize clarity, organization, and accessibility, with clear instructions and engaging materials. Instructors are encouraged to boost student engagement through interactive tools, real-life relevance, and adaptable teaching strategies tailored to online learning. Addressing technological challenges is also essential. This includes investing in infrastructure, providing technical support, and training faculty to manage Zoom effectively while considering issues like fatigue and privacy. Finally, as AI becomes more integrated into higher education, the lecturer's human value—expressed through care, emotional intelligence, and pedagogical skill—remains crucial and warrants further research.

Limitations

First, the online learning landscape continues to evolve rapidly. While these findings provide valuable insights into the initial transition to Zoom, student needs and preferences may have shifted further as both instructors and students have gained experience with online learning modalities. Also, it is important to note that these changes were novel and forced upon students and lecturers alike. Since then, learning online has become much more prevalent. Also, although the findings provide insight into synchronous online instruction more broadly, they emerge from Zoom-based teaching during a specific pandemic context and should be interpreted within those boundaries. Future studies should investigate how this rapidly changing teaching method has evolved since.

Second, although SET (Student Evaluations of Teaching)is an important source of information, it is somewhat biased. Although students gave a sense of their needs and vision about how online learning should look, other pedagogical issues should be considered because what the students want is not always what they need or what is academically appropriate. Future research should further explore the influence of these needs on other aspects of teaching such as achievement and implementation of the learned material in daily settings.

Additionally, SETs are also subject to well-documented biases, including potential gender bias, halo effects, grade-related evaluations, and the influence of affective reactions unrelated to instructional quality. As such, SET data do not provide an objective measure of teaching effectiveness. However, the present study does not treat SETs as evaluative metrics but as narrative artifacts that reveal students lived expectations and interpretations of synchronous learning. By analyzing a large corpus of anonymous open-ended responses

across two institutions, we sought to identify recurring patterns rather than individual-level judgments, thereby mitigating reliance on isolated evaluative comments.

In addition, several methodological considerations delimit the scope of our findings. First, the study was conducted in two higher-education institutions within a single national context, which may limit transferability to other countries or cultural settings where expectations regarding instructor–student interaction, authority, or privacy differ. Second, the analysis relies on voluntary SET responses, which introduces potential self-selection bias, as students with particularly strong positive or negative experiences may have been more likely to participate. Third, although responses were analyzed in their original language, translation for reporting purposes may have involved minor shifts in nuance. Fourth, the absence of demographic data prevents examination of how perceptions may vary across student populations (e.g., undergraduate vs. graduate students, disciplinary fields, prior online experience). Finally, the study is based exclusively on textual SET data and does not include triangulation with additional sources such as interviews, classroom observations, or learning analytics. Future research employing multi-method designs and more diverse institutional and cultural contexts would help refine and extend the present findings.

Conclusion

This study highlights the centrality of interpersonal presence, course structure, instructional professionalism, and the affordances/constraints of the technological medium in shaping students' synchronous online learning experiences. Students consistently valued lecturers who were responsive, caring, patient, and adaptable; clear and coherent course organization; intellectually engaging pedagogy; and streamlined, reliable use of platforms and materials. Together, these factors mitigate "transactional distance" and sustain attention and motivation in virtual settings.

Declarations

Ethics Approval

The research involved secondary analysis of anonymized open-ended responses from Student Evaluations of Teaching (SET) collected in two higher-education institutions. Institutional permission and Institutional Review Board (IRB) approval were obtained at both sites prior to data sharing and analysis. All datasets were de-identified before transfer; no student or instructor identifiers were retained. Given the use of existing, anonymized data, the IRBs granted a waiver of informed consent. The study adhered to relevant ethical guidelines for human-subjects research.

AI Use Statement

No generative artificial intelligence (AI) systems were used in the design, conduct, analysis, or writing of this study. Data handling, coding, interpretation, and manuscript drafting were performed by the authors.

Conflict of Interest Statement

The authors declare no conflicts of interest, financial or non-financial, related to the conduct, analysis, or reporting of this research. No external funding was received beyond standard institutional resources.

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Is Open, Distance, and Digital Education (ODDE) good for the environment?

A systematic review of carbon footprint studies

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Abstract
This study presents a systematic review of research on the environmental sustainability of Open, Distance, and Digital Education (ODDE), focusing on its carbon footprint. Although higher education institutions (HEIs) are expected to reduce greenhouse gas emissions, the environmental impacts of teaching and learning modes remain underexplored compared to campus operations. To address this gap, 17 studies published between 2002 and 2025 were examined. The evidence shows that ODDE typically generates far lower emissions than campus-based education, mainly through reduced travel and campus energy use and the benefits of centralized delivery. Landmark studies reported reductions of more than 80% compared to face-to-face teaching. Studies conducted during the COVID-19 pandemic confirmed significant savings but also highlighted rebound effects, as household energy use increased while campus facilities continued to consume resources. Emerging technologies, particularly generative AI, further complicate the picture due to their high energy demands. Overall, the evidence suggests that ODDE can contribute positively to reducing the carbon footprint of higher education. However, the small number of studies, lack of standardized methodologies for carbon footprint assessment (CFA), and limited attention to rebound effects constrain broader generalizability. Future research should systematically compare different delivery models across diverse institutional contexts and develop shared CFA guidelines. Strengthening the sustainability profile of ODDE is of critical importance, not only for the higher education sector but also for advancing global climate goals.

Keywords: Open, distance, and digital education; ODDE; Sustainability; Carbon footprint; Greenhouse gas emissions; Systematic review

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In the context of global warming and ongoing digitalization, scholars have increasingly questioned the environmental effects of educational technologies used in digital education and online learning (e.g., Macgilchrist, 2024; Selwyn, 2025). Generative AI applications are particularly resource-intensive, with considerable carbon footprints and other environmental effects. Bozkurt (2025), for example, reviewed their energy and water consumption and generation of electronic waste. This study focuses on the carbon footprint of online learning and its associated infrastructure, using the Sustainable Development Goals (SDGs) as a guiding framework.

The United Nations World Commission on Environment and Development, established in 1983, significantly shaped the contemporary understanding of sustainability. The commission's 1987 Brundtland Report, *Our Common Future*, provided a definition of sustainable development that "meets the needs of the present without compromising the ability of future generations to meet their own needs" (Brundtland, 1987, para. 27).

The 1992 Rio Declaration, issued at the United Nations Conference on Environment and Development, is regarded as a key milestone in advancing sustainability. Its action plan, Agenda 21, addresses the economic, social, and environmental pillars of sustainable development. It calls on countries to establish monitoring and evaluation systems, using indicators to track changes across all three dimensions. Protecting the environment and its ecosystems is central to sustainability because environmental constraints place limits on economic and social development. In September 2015, countries from across all continents adopted Agenda 2030, comprising the 17 SDGs and 169 targets. These goals apply to nations as well as organizations, including higher education institutions (HEIs).

Elkington (1994) extended the concept of sustainability to organizations. Elkington's Triple Bottom Line Model of Sustainability considers the potential impact of managers' decisions on organizational profits, people, and the planet. The main argument is that organizational leaders have a threefold fiduciary duty: they must pursue profits for shareholders, act responsibly toward people affected by their business, and safeguard the environment impacted by their operations. Applied to higher education, the "products" are graduates prepared to become responsible and critical members of society; the "people" are students and other members of university communities; and the system, through its operations, affects the environment.

HEIs should assume a leading role as sustainable institutions in the fight against climate change. They can lead by example and influence the attitudes of individuals and future decision-makers in business, politics, and academia (Filimonau et al., 2021). Reducing the environmental effects of human activity will require insights from social and psychological research to develop environmentally sustainable ways of living, with education playing a central role in promoting them (Campbell & Campbell, 2011).

However, HEIs require extensive operations that generate substantial carbon emissions. In some countries, legislation now mandates universities to reduce these emissions as part of the net-zero agenda. For example, in the UK, the Higher Education Funding Council (HEFCE) set

ambitious carbon reduction targets in line with the 2008 UK Climate Change Act, aiming to cut emissions by 83% by 2050 compared to 1990 baseline levels (see Caird et al., 2015).

Efforts have focused on reducing the energy use and emissions associated with campus operations, including travel, building operations, and energy sources (e.g., Patella et al., 2025; Versteijlen et al., 2017; Yin et al., 2022). However, these measures are only indirectly related to teaching and learning models. Although teaching is the core function of HEIs, few studies have examined the effects of different delivery modes. One exception is the SusTEACH methodology developed at the Open University UK (Caird et al., 2015; Carr et al., 2019).

This study focuses on different delivery formats and their associated carbon footprints and environmental effects. Teaching formats exist along a spectrum from face-to-face to fully online learning based on their degree of digitalization. We use the definition of Open, Distance, and Digital Education (ODDE) provided by Zawacki-Richter and Jung (2023):

> We conceptualize ODDE as an overarching term to refer to all kinds of learning and teaching processes in which knowledge and skill base of educational technology, digital media, and tools are used to present and deliver content, as well as facilitate and support communication, interaction, collaboration, assessment, and evaluation. Thus, ODDE is not monolithic in form. It includes various practices, from technology-enhanced education, to flipped learning and blended learning to fully online education. (p. 4)

Mark Nichols, president of the International Council of Open and Distance Education (ICDE), argues that ODDE is sustainable, "characterised by, one, a low carbon footprint and, two, long-term financial viability while providing a quality, reliable service" (Nichols, 2024, p. 228). The Green Campus Task Force report published by the European Association of Distance Teaching Universities (Ubachs et al., 2024) highlights green campus initiatives undertaken by European distance teaching universities:

> A "Green Campus" refers to a Higher Education Institution (HEI) campus that is designed, built, and operated in an environmentally sustainable manner. This can include a variety of initiatives such as energy efficiency, use of renewable energy sources, recycling and waste reduction programs, sustainable transportation options, and conservation of natural resources. Green campuses also often include green spaces, such as gardens and parks, which provide habitat for wild-life and opportunities for outdoor recreation for students, faculty, and staff. (p. 2)

This definition appears to be broadly applicable to any university, perhaps even more so to a campus-based institution. Although it strongly emphasizes environmental sustainability, it does not address the distinctive characteristics of ODDE or its positive and negative environmental effects. Regarding sustainability in HEIs, Lane (2025) notes that "the key to success is for a university or college to define sustainability for itself and build a unique strategy and structure which reflects its nature, context, and geography" (p. 8).

Asha Kanwar, former President of the Commonwealth of Learning (COL), emphasizes the need for more research in this area: "[…] distance education can reduce costs, improve

quality, and increase access and equity. But now we've got another dimension, the ecology dimension where we need more of research" (Johnson & Cefa, 2024, p. 7).

In their systematic review of carbon footprint assessment methods in HEIs, Valls-Val and Bovea (2021) note that no standardized methodology exists for assessing the carbon footprint of educational institutions. They emphasize that "no specific reviews have been done for educational activities" (p. 2525), that is, teaching operations.

Against this background, this systematic review addresses the following research questions:

- RQ1 Publication and authorship patterns: How has the number of studies on the environmental impact and carbon footprint of ODDE developed over time, in which journals and other publication outlets are they published, who are the leading authors and what is their country of origin?
- RQ2 Carbon footprint assessment (CFA): What methods and factors are used to measure the carbon footprint of ODDE, and which type of HEIs are involved? What results are reported regarding the carbon footprint of ODDE, and in comparison, to on-campus face-to-face teaching and learning?

Put simply, we want to examine whether ODDE is good for the environment and what it can contribute to combating climate change.

Before outlining the methodology of our systematic review and presenting our results, we will first provide a brief overview of already published systematic reviews on the general topic of sustainability and environmental impacts in higher education and explain how our review differs from them.

Previous Reviews on Sustainability and the Environmental Impact of Higher Education

To start with, some reviews focus broadly on the impact of higher education on the SDGs and sustainable development. The first is Findler et al. (2019), who developed a sustainable development impact framework of HE institutions, highlighting direct and indirect impacts (e.g. greenhouse gas emissions caused by operations and contribution to climate change) based on 113 articles published between 2005 and 2017. They highlight the need to analyse existing sustainability assessment tools in HE regarding their ability to effectively examine the impacts of HEIs on sustainable development.

In this regard, Basheer et al. (2024) explored sustainability assessment practices in HE by means of a content and bibliometric analysis of 83 articles from 2018 to 2023. They provide a comprehensive overview of holistic sustainability assessments (e.g. studies on frameworks and tools, sustainability indicators) and also focus on the environmental dimension with studies on green campus initiatives, environmental sustainability, and carbon footprint assessment, and

sustainable mobility. However, an assessment of the teaching operations plays no or only a very minor role here.

Qiu and Dong (2024) explore the existing research on environmental impacts generated from the entire life cycle stages of campuses based on 135 articles published between 2003 and 2023. According to the Greenhouse Gas (GHG) Protocol, three scopes of direct and indirect GHG emissions are distinguished: Scope 1 direct emissions (e.g. on-campus use of natural gas for heating and cooling), Scope 2 indirect emissions (e.g. purchased electricity), and Scope 3 other indirect emissions (e.g. student and staff transportation). Qiu and Dong (2024) found that the majority of studies focused on Scope 1 and Scope 2 emissions, with only eight articles analysing Scope 3 emissions. They therefore suggest incorporating Scope 3 emissions into the life cycle analysis of carbon assessments.

Umar et al. (2024) carried out a bibliometric mapping review of publication trends in sustainability and HE. Their corpus included 262 articles over a one-year period. Most articles were coming from European countries and the USA, but only few from Asian countries. The journal with the highest number of publications was the *Journal of Sustainability*, followed by the *International Journal of Sustainability in Higher Education*, and the *Journal of Cleaner Production*. They note that the sustainability performance assessment has gained momentum in the post-COVID-19 period.

There are three other systematic reviews from 2020, 2023, and 2024 that have specifically addressed the carbon footprint of HEIs. The review by Valls-Val and Bovea (2021) has already been mentioned; it is based on 35 papers and primarily calls for a specific methodology with standardized factors for the carbon footprint assessment of HEIs. Like Qiu and Dong (2024) they also found that many institutions have accounted for just Scope 1 and 2 in their carbon footprint reports because they are the easiest and cheapest to assign and calculate. They note that quantifying Scope 3, other indirect emissions, can be quite challenging for HEIs.

Another bibliometric analysis on research trends of universities' carbon footprint was carried out by Ma et al. (2023). They note that an accurate assessment of carbon footprint is one of the key elements to evaluate progress towards sustainable development. The bibliometric dataset contained 273 publications between 2009 and 2022. Based on a content analysis, they conclude that future research should focus on analytical frameworks, sustainable commuting, eco-recycling, green curriculum, energy consumption behavior, and energy conservation.

The most recent systematic review was published by Paredes-Canencio et al. (2024) based on 50 articles and reports up to 2022. They confirm the finding of previous reviews that the majority of studies focus on Scope 1 and 2 emissions. The most evaluated emission sources were the consumption of electrical energy (78%), transportation (74%), and the use of fuels (64%). They also call for a specific carbon footprint guideline for universities that would improve the carbon footprint assessment and would allow better comparisons between HEIs.

Based on the current literature we can conclude that, on the one hand, there are systematic reviews that take a very general and broad approach to the topic of university sustainability, considering not only environmental but also social and economic dimensions. On

the other hand, there are several systematic reviews that focus specifically on the carbon footprint of universities, though their emphasis lies on campus operations rather than on the actual teaching and learning processes, and the teaching modes of delivery, and the associated direct and indirect environmental impacts. Our aim with this systematic review is to help close this gap, and in the following, we describe our methodological approach.

Method

A systematic review seeks to address well-defined research questions through a transparent and replicable search strategy, applying explicit inclusion and exclusion criteria to determine eligible studies (Gough et al., 2017; Zawacki-Richter et al., 2020). Data from the included studies are subsequently coded and extracted to synthesize findings and identify gaps or inconsistencies. Following established methodological guidance (Newman & Gough, 2020), the process involves formulating the review question and protocol, defining eligibility criteria, designing the search strategy and identifying information sources, screening studies against the criteria, presenting search results in a flowchart, extracting descriptive data, appraising study quality, and synthesizing the evidence. This structured approach enhances both transparency and reproducibility.

The protocol for this review (including a RIS-file containing bibliographic information for all 17 articles) was registered and published on the Open Science Framework (OSF) platform (https://osf.io/) and is available via the following link: https://osf.io/jcrup/.

Search Strategy and Data Retrieval

The authors formulated a broad search string (see Table 1) for this systematic review to retrieve relevant studies. The articles were retrieved from four international databases: Education Source, Scopus, Web of Science, and IEEE Xplore. By selecting these databases, we were able to ensure that both studies from the field of education and more technically oriented work were captured. In particular, the IEEE Xplore database provided numerous results from conference proceedings in the engineering sciences.

Table 1

Search String

Topic	Search string
Study focus	(carbon OR ecological OR sustainab* OR "greenhouse gas") NEAR/3 (emission OR report* OR assess* OR footprint OR impact)
	AND
Education level	("higher educat*" OR universit* OR college OR post-secondary)
	AND
ODDE	(digital OR distance OR online OR mobile OR open) NEAR/3 (edu* OR program* OR teach* OR learn*)

The inclusion and exclusion criteria (see Table 2) for this systematic review specified four key dimensions for inclusion and exclusion: publication year, publication language, education level and setting, and the document type. No time limit was set to include studies from all available years, provided the studies addressed higher education involving ODDE interventions.

To maximize the retrieval of studies that might include carbon emission calculations, the review included journal articles, conference proceedings, and book chapters. Short reports, editorials, commentaries, and letters were excluded, as were any studies that explicitly fell under the review methodology category (i.e. systematic reviews, scoping reviews, or other literature reviews).

Table 2

Inclusion and exclusion criteria

Criteria	Inclusion	Exclusion
Time	no limit	-
Language	English	not in English
Education level	higher education	early childhood education, K-12, non-formal, informal education
Education setting	open, distance, and digital education (ODDE)	not related to ODDE
Intervention	carbon emission calculations involving ODDE	carbon emissions in conventional campus settings only; studies focusing on learning about sustainability; classes aiming to foster environmental sustainability through engineering or architecture; awareness-raising interventions for environmental sustainability
Scope	environmental sustainability	other sustainability domains (e.g., social, economic)
Document type	journal articles, conference proceedings, book chapters	reports, editorials, commentaries, letters

Screening and Coding Process

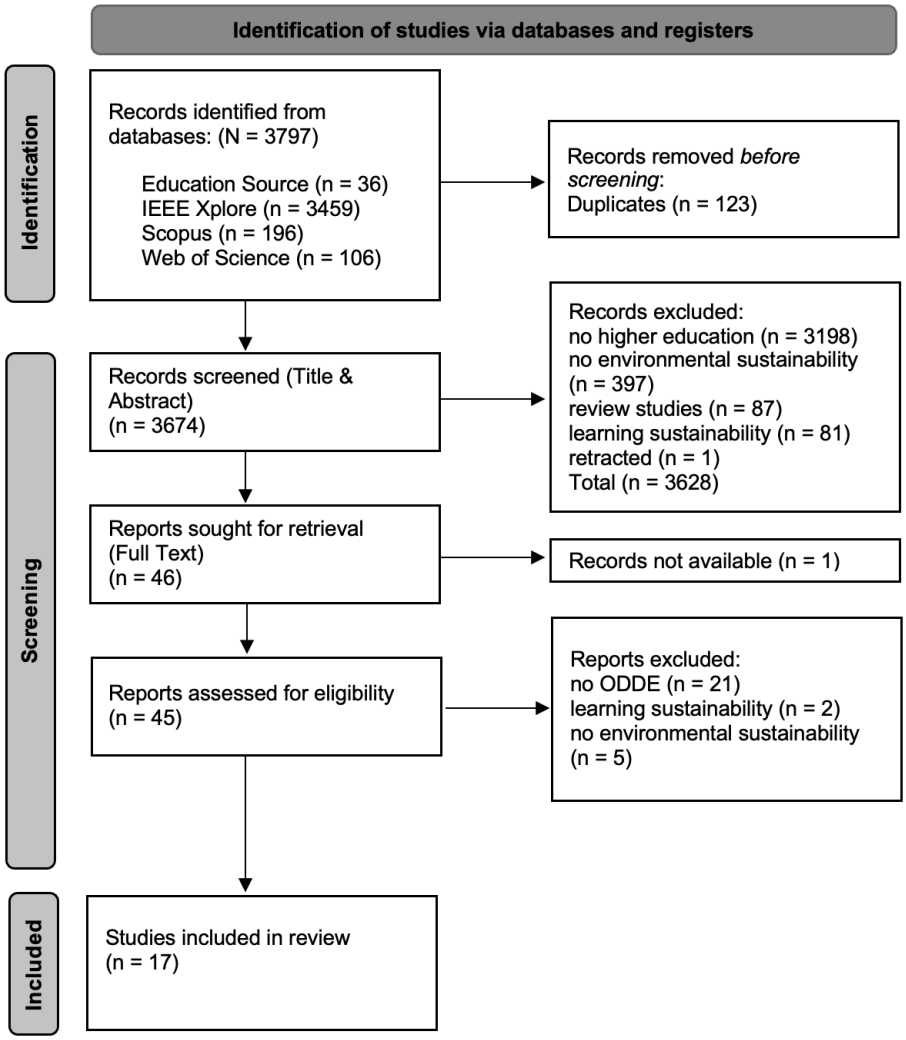
After alignment discussions among three coders on the duplicate-clean data set (N = 3,674), a blind Abstract and Title Screening (A&T) review was conducted on a randomly selected sample of 100 studies. After the initial screening, the Fleiss' κ agreement was $\kappa = 0.50$, which was lower than expected due to differing interpretations of "environmental sustainability." Following a reconciliation meeting, a second round of screening was conducted on a new sample, resulting in only one inclusion decision. Although there was full agreement on this second sample, the authors opted to repeat the process using a purposefully selected sample from the corpus. This was because the IEEE Xplore database returned many articles unrelated to higher education alongside relevant ones.

For the third round, 100 studies most relevant to higher education were sampled, and coders achieved perfect agreement ($\kappa = 1.00$). The proportion of inclusion and exclusion

decisions became more balanced compared to earlier rounds, though exclusions still predominated. The authors recognized that κ – whether Cohen's κ for two raters (Cohen, 1960) or Fleiss' κ for multiple raters (Fleiss, 1971) – measures agreement beyond chance by comparing observed agreement to expected agreement based on marginal category proportions. This adjustment can sometimes produce the "asymmetry problem" (also called the prevalence paradox), in which κ is low despite high raw agreement if one category (e.g., "exclude") is chosen far more often (Byrt et al., 1993; Randolph, 2005).

Figure 1

PRISMA Flow Diagram, slightly modified Moher et al. (2009)



To minimize the influence of chance agreement, the authors conducted a fourth and final round of screening. This round again yielded perfect agreement among the three raters, with κ = 1.00 and a 100% raw agreement rate. Since the observed and expected agreements were identical

in the sense of no prevalence imbalance, there was no paradoxical situation in this final test, and the authors retained the final κ calculation as representative of the subsequent A&T screening, which the authors conducted individually.

After A&T screening, the tentative coding scheme was finalized, and full texts were retrieved. Following a Cohen's κ calculation (κ = 1.00) confirming perfect agreement on the finalized scheme, coding proceeded individually by the authors. Despite the rarity of achieving such agreement, the coders concluded this was due to the specificity of the review questions. The coding scheme included categories capturing the corpus characteristics (e.g., publication year, journal, country), the carbon emission calculation approaches employed, the factors included in these calculations (such as energy consumption, transportation, material use), and the data sources from which calculation inputs were drawn. This structured approach ensured that coding decisions were consistently anchored in the agreed-upon definitions and categories, maintaining reliability throughout the full-text analysis and subsequent synthesis.

The software tool Rayyan was used to support the entire screening process, while data extraction for the 17 included studies was conducted using an Excel spreadsheet.

Limitations

To the best of our knowledge, this study covers all relevant studies within our research scope in this area. However, as with any research, this study is subject to certain limitations. The first limitation concerns language. If relevant studies were published in local databases in the home-country language, they could not be retrieved, as the search was conducted in English. The second limitation is the database scope: the review was restricted to four databases, one of which is particularly strong in engineering and natural sciences and provided a substantial yield, but others may contain relevant studies that were not captured. A related constraint involves document type in relation to publication language. Although dissertations and theses were not intentionally excluded, some relevant works may remain in local repositories in non-English languages and thus were not indexed in the selected databases.

Finally, the inclusion criteria themselves also limited the scope: the study aimed to identify what ODDE might contribute to CO_2 emission policies, so carbon emission studies based solely on conventional education, without reference to off-site practices, were excluded. While these were outside the review's scope, they could still offer useful insights into theoretical frameworks and calculation approaches applicable to fully on-site systems.

Results and Discussion

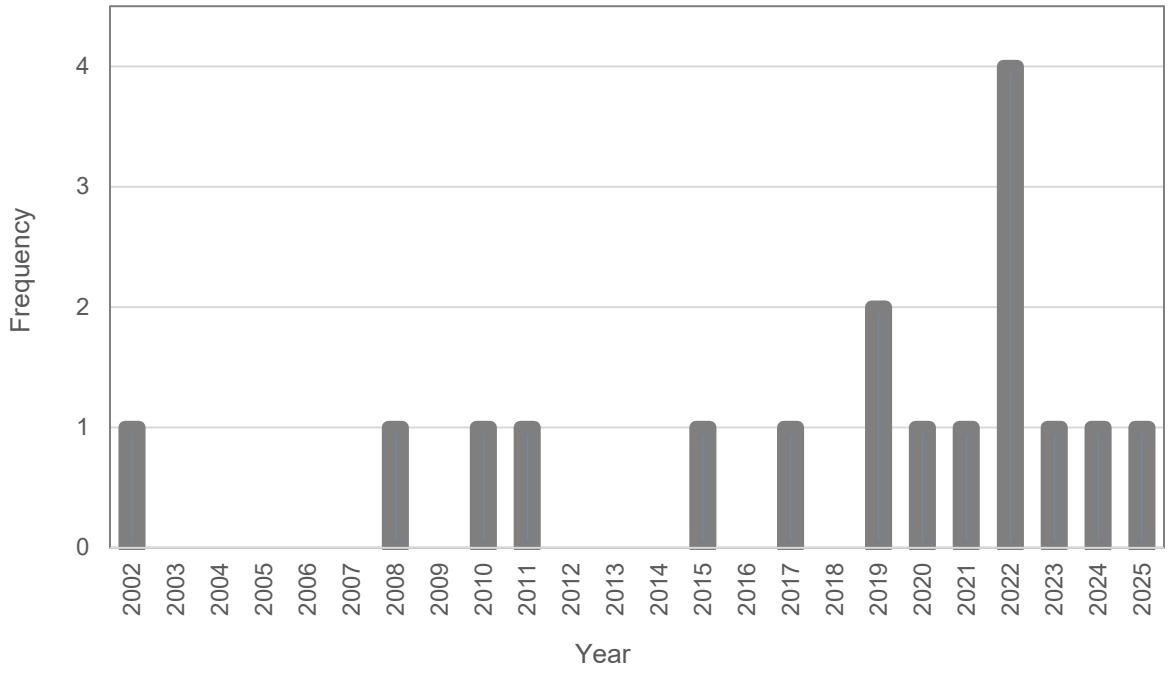
RQ1: Publication and Authorship Patterns

Publications per Year

Figure 2 shows the number of papers per year from 2002 to 2025. The distribution indicates that the topic of environmental sustainability related to ODDE has been scarcely addressed in the literature. Until 2018, only a few articles on the topic were published. It was only from 2019 onwards that articles began to appear annually, with the peak occurring in 2022 at four publications. The relative concentration of publications in 2022 suggests that these studies were conducted during the COVID-19 pandemic and likely focused on examining the effects of lockdowns and emergency remote teaching on the carbon footprint of universities.

Figure 2

Number of Included Articles per Year (N = 17)



Publication Types

The majority of the studies (n = 15) were published in academic journals. Two articles were published in the *International Journal of Sustainability in Higher Education*, other journals included the *Environmental Impact Assessment Review*, the *Online Journal of Distance Learning Administration*, *Current Opinion in Environmental Sustainability*, *Sustainability (Switzerland)*, and *Environmental Research: Infrastructure and Sustainability.* One study was published as a book chapter and one in the *IOP Conference Series: Earth and Environmental Science*.

Countries

For the analysis of the country-wise distribution of articles, the first author's country was considered (n = 12 countries). Most studies originated in Great Britain (n = 5) and the United States (n = 2). The following countries each contributed one study: Australia, China, Indonesia, Italy, the Netherlands, the Philippines, South Africa, Spain, Thailand, and Turkey.

Leading Authors

The authors who published the most studies on this topic were all affiliated with the same research institution in the United Kingdom: the Department of Engineering and Innovation at the Open University. They published together until 2015. Four authors were each involved in three publications, including Sally Caird, Andy Lane, Robin Roy, and Ed Swithenby. Stephen Potter contributed to two articles.

RQ2: Carbon Footprint Assessment (CFA) in Relation to ODDE

All studies included here examine the carbon footprint of HEIs with regard to institutional organization or the provision of courses and programs in ODDE formats. Table 3 provides an overview of the study settings, thematic scopes, methodological approaches, and results. Studies from open and distance teaching universities are particularly well represented, including the Open University UK (GB), the Open Universiteit (NL), and the University of South Africa (ZA). Of the 17 studies, 14 conducted their own carbon footprint assessment (CFA) to compare different delivery formats or the impact of specific teaching operations; these will be discussed in detail below.

The following three studies (Versteijlen et al., 2017; Jarillo et al., 2019; Louw, 2022) did not conduct their own CFAs or calculate emissions but instead discussed various aspects of the carbon footprint of higher education in relation to ODDE.

Versteijlen et al. (2017) from the Open University of the Netherlands discuss the advantages and disadvantages of online education as a measure to reduce the carbon emissions of HEIs in the Netherlands. They draw on the classification of greenhouse gas emission sources according to the GHG Protocol (WBCSD/WRI, 2015) and analyze GHG reports from various Dutch universities. Their results focus on Scope 3 emissions (student and staff commuting and travel). Based on the literature review, they conclude that online education could make a significant contribution to reducing the carbon footprint: "Another strategy to reduce student travel emissions is the use of online education, and this seems to have great potential" (p. 82). Against this background, the authors discuss the advantages and disadvantages of online learning based on qualitative expert interviews. The emphasis, however, is not on the environmental impacts of online learning, but rather on pedagogical aspects, including the interaction between students and instructors, among students themselves, and between students and the presented learning materials.

In a conceptual paper, Jarillo et al. (2019) discuss the challenges and opportunities of online higher education in relation to SDG 4 (quality education), SDG 10 (reduced inequalities),

and SDG 13 (climate action). The article therefore also addresses broader issues of equitable access to high-quality education through flexible online education. With regard to SDG 13, the authors consider the carbon footprint of an HEI in a case study of an online university with approximately 42,000 students. However, the analysis relies solely on emission measures reported in the literature, which are applied to the case. This approach yields only a rough estimate of the potential CO_2 savings achievable through online delivery.

Louw (2022) used a case study and employee survey at a very large distance teaching university in South Africa to investigate staff commuting patterns (Scope 3 emissions) and discuss the findings in relation to policies intended to promote telecommuting (i.e., working from home) and thereby reduce traffic-related emissions. The reported level of telecommuting was very low: 81.5% of respondents reported commuting to campus five days a week, and, of greater concern, more than 80% indicated that they did not carpool but instead drove alone.

Two Phases of CFA

The 14 studies that conducted and calculated a CFA can be divided into two phases over time. The first phase, covering the years 2002 to 2019, includes six studies that examined the carbon footprint of different delivery modes or calculated emissions from specific factors, such as printing study materials or student commuting behavior. The second phase was driven by the COVID-19 pandemic starting in 2020, during which reduced CO_2 emissions resulting from lockdowns and emergency remote online teaching were compared with pre-pandemic campus operations. This phase comprises seven studies, all conducted at conventional campus-based universities. In addition, one further article analyzes emission savings from online examinations at a distance teaching institution during the pandemic.

Phase 1 –Carbon Savings from Distance and Online Learning (2002–2019)

The first phase is dominated by a group of scholars at the Open University UK (OUUK), who, in two successive projects (the Factor 10 Vision Project and the SusTEACH Project), developed and applied the SusTEACH methodology to conduct an environmental assessment of courses using digital technology, face-to-face, and print-based teaching methods. UK legislation mandates universities to reduce carbon emissions as part of the net-zero agenda. In line with the 2008 UK Climate Change Act, the Higher Education Funding Council (HEFCE) set targets to reduce carbon emissions by 83% by 2050 compared with 1990 baseline levels.

Herring and Roy (2002) report on the Factor 10 Vision Project in which the environmental impacts of three different modes of UK higher education were compared: two conventional campus-based courses, a conventional print-based distance education course, and an electronically delivered distance education course. Energy consumption and CO_2 emissions were used as proxies for key environmental impacts. For comparability, all results were normalized per student per 10 CATS points, based on the UK Credit Accumulation and Transfer Scheme (1 CATS ≈ 10 study hours; 360 CATS for an undergraduate degree). The study revealed that OU conventional print-based courses used nearly 90% (factor of 10) less total energy and CO_2 emissions per student per 10 CATS points compared to the conventional campus-based courses, largely due to the elimination of commuting and reduced campus site energy

consumption. The latter benefits from economies of scale in teaching thousands of students from a single central campus. Furthermore, e-learning, as implemented by the OUUK at that time, did not appear to lower total energy use and CO_2 emissions compared to print-based distance learning; in fact, the electronically delivered and tutored course required over 25% more energy and emissions per student per 10 CATS points.

A similar study employing the same methodology was conducted by Roy et al. (2008) with an expanded sample of 20 courses: 10 full-time and 3 part-time face-to-face campus courses, 3 part-time print-based courses, and 4 part-time online courses. The earlier findings were confirmed: Distance learning courses use 87% less energy and produce 85% fewer CO_2 emissions than full-time campus-based courses. Part-time campus courses achieved reductions of 65% in energy use and 61% in emissions compared with full-time campus courses. These lower impacts are largely attributable to reduced student travel, the elimination of much of the energy consumption associated with student housing, and more efficient campus site utilization. E-learning offers only modest additional reductions–20% in energy use and 12% in emissions–over primarily print-based distance learning, largely due to the higher energy demands of computing and increased paper use for printing.

Building on this previous work, the SusTEACH project further developed the methodology and applied it to 30 courses and modules from 15 different HEIs in the UK (Caird et al., 2015). The sample also included the 20 courses from the Factor 10 Vision Project, which were reanalyzed using the enhanced methodology. The study distinguishes between five different teaching models: the face-to-face teaching model, the distance teaching model, the online teaching model, and the ICT-enhanced distance teaching model and ICT-enhanced face-to-face teaching model. Energy consumption and CO_2 emissions were calculated for travel, ICTs, paper, print and other materials, residential energy, and campus-site operations.

The study found that distance education teaching models (paper-based, ICT-enhanced, and online) used on average 88% less energy and produced 83% fewer carbon emissions than campus-based models (face-to-face and ICT-enhanced face-to-face). The lowest impacts were recorded for online teaching, with 363 MJ of energy use and 36 kg CO_2 per 10 CATS points, representing reductions of 27% (online) and 21% (ICT-enhanced distance) compared with print-based distance teaching, largely due to lower material use and transport needs. In campus systems, ICT enhancement reduced carbon emissions by only 11% and had little effect on energy consumption, as ICT mostly supplemented rather than replaced in-person teaching. Overall, travel emissions accounted for the largest share of the emissions from the 30 courses examined (approximately 40%), although there were substantial differences between the various teaching models.

Finally, the SusTEACH method was also applied in a comparative study in Botswana (Carr et al., 2019). They compared a Bachelor of Business Administration program at the Botswana Open University (in which course content was distributed via CDs) with a program at the Botswana Accountancy College, a residential institution, and found that, on average, the carbon footprint of the face-to-face mode was nearly three times greater than the distance modality.

Table 3

Overview of Included Studies by Year (N = 17), Phase 1

Author(s)	Year	Ctry[1]	HEI type[2]	Measurement and Scope	Results
Herring & Roy	2002	GB	ODL	Comparison of print-based distance education vs. e-learning vs. f2f campus-based education; Scope: ICT energy, electricity, course-related travel, computer purchase and use, paper consumption, residential heating	Print-based distance vs. face-to-face campus: 90% less energy, 90% fewer CO_2 emissions; e-learning vs. print-based distance: 25% more energy, 25% more CO_2 emissions
Roy et al.	2008	GB	ODL	See Herring & Roy with an extended sample, including part-time courses	Distance learning vs. full-time campus: 87% less energy, 85% fewer CO_2 emissions; part-time campus vs. full-time campus: 65% less energy, 61% fewer CO_2 emissions; online vs. print-based distance: 20% less energy, 12% fewer CO_2 emissions
May et al.	2010	US	on-campus	Online courses; Scope: Student printing behaviour	47.05 t less CO_2 emissions over one year
Campbell et al.	2011	US	on-campus	Online courses; Scope: Student commuting	Ranging between 0.7 and 9.5 t less CO_2 emissions per course over the semester
Caird et al.	2015	GB	ODL	Comparison of print-based distance education vs. online learning vs. f2f campus-based education, including ICT-enhanced modes of distance and online learning; SusTEACH method; Scope: travel, purchase and use of ICT devices, books and publications, use of paper, home energy use, campus site operations	Distance education (paper-based, ICT-enhanced, online) vs. campus-based: 88% less energy, 83% fewer CO_2 emissions; online vs. print-based distance: 27% less energy, 27% fewer CO_2 emissions; ICT-enhanced distance vs. print-based distance: 21% less CO_2 emissions; total travel emissions share: ~40%
Versteijlen et al.	2017	NL	ODL	No CFA, review of Scope 3 emissions of Dutch HEI	Pros and cons of online learning
Carr et al.	2019	GB	ODL	Comparison of online learning vs. f2f campus-based education; see SusTEACH method (Caird et al., 2015)	Campus-based vs. online: three times higher CO_2 emissions
Jarillo et al.	2019	ES	ODL	No CFA, review HEIs impact on SDG 4, 10 and 13, and carbon footprint in HEI, case study on Int. University of La Rioja (41,870 students)	Estimates of CO_2 emission savings based on the literature

Table 3 (continued)

Overview of Included Studies by Year (N = 17), Phase 2

Filimonau et al.	2021	GB	on-campus	Comparison during COVID-19 pandemic, 2018-2019 vs. 2020, institutional data and interviews, Scopes 1-3	29% fewer CO_2 emissions in 2020; 45% electricity savings on campus; 51% gas consumption savings on campus; 73% share of emissions from learning and working from home
Salamena et al.	2021	ID	on-campus	Comparison COVID-19 pandemic, 2019 vs. 2020, Indonesia and Japan, institutional data and surveys, transportation and electricity consumption, Scopes 2 and 3	Emissions in 2019 (Indonesia: 549 t CO_2/; Japan 752 t CO_2), online learning emissions in 2020 (Indonesia: 10 t CO_2/; Japan 8.9 tCO_2); 96% transportation share
Yin et al.	2022	CN	on-campus	Comparison COVID-19 pandemic, 2011-19 vs. 2020, eight Chinese universities, institutional data, transportation and electricity consumption, Scopes 2 and 3	732 kt fewer CO_2 emissions from electricity consump-tion; 504 kt fewer CO_2 emissions from reduced transportation
Cortes et al.	2022	PH	on-campus	Comparison COVID-19 pandemic, 2019 vs. 2020, own GHG Inventory, University of the Philippines, Scopes 1-3	60.9% fewer CO_2 emissions in 2020
Heller et al.	2022	AU	on-campus	Comparison of f2f campus-based education vs. online; cohort of 128 international students; Scope 3: air travel, International Civil Aviation Organization (ICAO) carbon emissions calculator	969 t CO_2 emissions savings
Louw	2022	ZA	ODL	No CFA, review of Scope 3 emissions, survey, commuting of staff at the University of South Africa vs. home office (telecommuting)	Almost complete lack of telecommuting, >80% of vehicles carry only one person
Gümrükçüoğlu et al.	2023	TR	on-campus	Comparison COVID-19 pandemic, 2019 vs. 2020, institutional data, Scopes 1-3, emissions resulting from homework and study not included	47% fewer CO_2 emissions in 2020, mainly due to electricity savings
Prasara-A et al.	2024	TH	on-campus	Comparison COVID-19 pandemic, 2015-19 vs. 2020-21, TGO (2018) guidelines, Scopes 1-3	Annual per capita emissions (2015-2019: 0.35–0.37 t CO_2e; 2020-2021: 0.29 t CO_2e), electricity share (39-41%); 17-22% reduction; Scope 3 normal years (83–97 t CO_2e), 2020 (35 t CO_2e), 2021 (17 t CO_2e)
Patella et al.	2025	IT	ODL	Comparison COVID-19 pandemic, focus on impact of online exams, Scope 3, transportation	9,000 tCO_2e potential savings

Note.[1] International country code according to ISO 3166-1 alpha2; [2] ODL = Open and distance learning; on-campus = residential, campus-based learning

In the period 2002-2019, two further studies from authors from campus-based HEIs in the United States are available. Also referring to Elkington's Triple Bottom Line Model of Sustainability, May et al. (2010) examined the environmental impacts of online learning at the University of Dallas, focusing on a specific aspect: the printing behaviors of online students, based on 92 online course sections offered in an MBA program. Students were asked to estimate the proportion of downloadable documents and other printable materials they would normally print during an online class. To measure the environmental impact of printing, they used the Hewlett-Packard (HP) Carbon Footprint Calculator, which was designed to assess organizational printing activities. The students' responses were used to estimate the proportion of pages that would not be printed during each term. The authors conclude that the environmental benefits included saving 65,487 kW of energy, preventing the emission of 47.05 tons of CO_2, which is the equivalent of about 10 round-trip flights between New York and Los Angeles.

Campbell and Campbell (2011) also looked at a specific source of CO_2 emissions from online courses offered by three HEIs in California. To calculate emission savings from online courses, 500 students were asked in a survey about their usual mode of transportation to campus, miles per gallon used (if they drove), and their distance from campus. Total miles not driven were used to calculate savings in CO_2 emissions. Based on the commuting behaviour, the total mitigation of CO_2 ranged between 0.7 and 9.5 tons over the semester.

Phase 2 – COVID-19 Lockdown Impact Comparisons (2020–2025)

The second phase is characterized by articles examining changes in energy consumption and CO_2 emissions resulting from the lockdowns and the sudden shift to emergency remote online teaching during the COVID-19 pandemic. Six studies were published in this period, all conducted at traditional campus-based universities. In contrast to the first phase, where studies examined the impact of different teaching models or specific aspects of online education, the second-phase studies conduct carbon footprint assessments of entire higher education institutions, applying organizational boundaries in accordance with Scopes 1, 2, and 3 of the GHG Protocol.

The first study was conducted by Filimonau et al. (2021). It compares the carbon footprint of 2018 and 2019 with that of the first year of the pandemic in 2020 at Bournemouth University in the UK. The analysis draws on institutional data and interviews with students and staff to capture home-working conditions. Emissions were calculated using an input–output model, in accordance with the UK Government's guidance on corporate GHG reporting, covering Scopes 1, 2, and 3 emissions. During the lockdown, the carbon footprint decreased by about 29%, with the largest share of emissions (73%) arising from learning and working from home. Savings on campus were smaller than expected (45% in electricity use and 51% in gas consumption), indicating that even when the campus is not used, substantial energy is still required to maintain its operations.

The authors point to a significant rebound effect: Since working or studying from home can produce a carbon footprint comparable to commuting to the university, much of the carbon savings gained from moving education online to reduce student and staff travel can be largely

offset. Referring to the SusTEACH studies and Versteijlen et al. (2017) in Phase 1, the authors note that online learning is not as environmentally friendly as suggested here. However, it should be noted that distance teaching universities serve large student populations from a small, centralized campus and are not directly comparable to large campus-based universities.

Salamena et al. (2021) compared the differences in CO_2 emissions between 2019 and 2020 for students in Japan and Indonesia. However, the study only considered electricity consumption and transportation.

In Indonesia, face-to-face learning resulted in at least 549 t CO_2 emissions per academic year, while in Japan, emissions reached 752 t CO_2 per year. In both countries, transportation was the largest contributor, accounting for approximately 96% of total emissions. During online learning, Indonesian students produced around 10 t CO_2 per year, and Japanese students emitted 8.9 t CO_2 per year, representing a substantial reduction compared with traditional in-person education. However, unlike Filimonau et al. (2021), the authors did not account for the fact that campus operations continue to consume substantial energy even when the facilities are not used. Therefore, the reported effects are likely to be significantly smaller.

Yin et al. (2022) focused on two sources of emissions—transportation and electricity consumption—and compared usage over the period from 2011-2019 with that of 2020 at eight Chinese universities. The study uses central institutional data and follows the *Guidelines on Enterprise Greenhouse Gas Emissions Accounting and Reporting-Power Generation Facilities*, issued by China's Ministry of Ecology and Environment. The authors conclude that the shift to online learning during the pandemic resulted in an unexpectedly large reduction in CO_2 emissions. The carbon emissions avoided through online Education amounted to 732 kt CO_2 from reduced electricity, and 504 kt CO_2 from reduced transportation.

At the University of the Philippines (UP), Cortes et al. (2022) compared the carbon footprint of 2019 with that of 2020, using a GHG inventory developed by the authors in 2018. In 2020, total CO_2 emissions were estimated at 555.8 t CO_2e, representing a 60.9% reduction compared with 2019. Per capita emissions in UP were 0.9 t CO_2e in 2019 and 0.3 t CO_2e in 2020, both remaining below the national average. The pandemic led to substantial emission reductions across most activities, except for fuel-related emissions, which rose by 305.8%. The increase in Scope 3 fuel consumption was due to the decision of the university to provide a shuttle service between two campuses during the lockdown when public transportation was not available.

Heller et al.'s (2022) study is only about travel impacts of international students at a university in Manchester in the UK that did not take place during the pandemic. Using the International Civil Aviation Organization (ICAO) carbon emissions calculator, they estimated the savings in CO2 emissions by a cohort of 128 master's students who studied fully online from their home countries rather than traveling to and living in Manchester to attend the university in person. The savings accumulated to 969 t of CO2.

In a study from Turkey, Gümrükçüoğlu et al. (2023) calculated the carbon footprint for a campus with over 50,000 students and more than 2,000 staff members for the years 2019 and

2020. In 2020, total emissions were 47% lower, primarily due to reduced electricity consumption. However, emissions resulting from home working were not included in the assessment.

Finally, Prasara-A et al. (2024) assessed the carbon footprint of a university in Thailand, with over 40,000 students for 2015-2021 following TGO (2018) guidelines, covering Scopes 1-3 emissions. From 2015-2019, annual per capita emissions ranged between 0.35–0.37 t CO_2e, with electricity (Scope 2) as the largest source, accounting for 39–41% of total emissions. During 2020–2021, per capita emissions fell to 0.29 t CO_2e—a 17–22% reduction. Scope 3 emissions (water, paper, and staff/student transport) dropped sharply from 83–97 tCO_2e in normal years to 35 t CO_2e in 2020 and 17 t CO_2e in 2021, with student transport being the main contributor in 2020.

Two further studies are included in Phase 2. Louw (2022) did not conduct their own CFA and was therefore discussed earlier in this section. Patella et al. (2025) explored the opportunities of online exams to avoid car trips. The study employed a survey-based case study method with 8,356 responses from students in Italy. The results indicate that 37% of private motorized transport users, including car and motorbike drivers, might consider shifting to rail, while 37% of car users are open to carpooling. Despite this, cars remain the most commonly used mode, accounting for 51% of travel, with an estimated 40 million vehicle-kilometers traveled annually, producing approximately 9,000 t of CO_2 equivalent that could be avoided.

Standards and Operational Boundaries of Recent Carbon Footprint Studies

Regarding the implementation and organizational boundaries of the CFA, a heterogeneous picture emerges. Different reference values for CO_2 emissions are sometimes used, and varying aspects are considered. In some cases, campus operations during lockdowns were included in the calculations, while in others they were not; similarly, the energy consumption of students and staff working from home was sometimes taken into account and sometimes omitted. As previously noted by Valls-Val and Bovea (2021), there is no standardized methodology for CFAs, particularly when different teaching models are taken into consideration.

In line with the GHG Protocol (WBCSD/WRI, 2015), we distinguish between direct emissions, owned or controlled by the organization, and indirect emissions, which are a consequence of the organization's activities but occur at sources owned or controlled by another party, such as students. To clarify the distinction between direct and indirect emission sources, enhance transparency, and ensure relevance for various types of organizations as well as diverse climate policies and business objectives, greenhouse gas accounting and reporting categorize emissions into three defined "scopes": Scope 1 direct emissions (e.g., on-campus use of natural gas for heating and cooling), Scope 2 indirect emissions (e.g., purchased electricity), and Scope 3 other indirect emissions (e.g. student and staff transportation, emissions from suppliers, wastewater, water supply, solid waste, and paper used). Valls-Val and Bovea (2021) and Qiu and Dong (2024) found in their reviews, that many HEIs accounted for just Scopes 1 and 2. Calculating other indirect Scope 3 emissions can be challenging because they are not under direct control of the organization.

How do the studies in our corpus compare, looking at the studies from Phase 2? Filimonau et al. (2021) advise caution when comparing current carbon footprint data with studies that are a decade or more old, as substantial progress has recently been made in the sustainability performance of higher education institutions. We find that all nine studies from Phase 2 included Scope 3 emissions related to the impact of ODDE (see also Table 3).

Conclusion and Implications

With this systematic review, we hope to have provided a solid initial overview of the carbon footprint of ODDE. The results are diverse, but considering the great importance of this interdisciplinary topic, only limited research is available to date. Over a period of nearly 25 years, only 17 relevant studies could be identified. Due to this scarcity and the lack of standardized methods for CFA in HEIs, a quantitative aggregation of the impact of ODDE on the carbon footprint through meta-analysis is not possible.

We hold the SusTEACH studies in high regard. However, they already date back quite some time. Filimonau et al. (2021) reiterate the need for further research on the impact of different teaching models:

> […] a dedicated stream of research is necessary to investigate and compare the carbon implications of different teaching/learning modes such as fully offline, blended, fully online. Although this current study has provided some initial evidence towards the GHG emissions of online education, this evidence should be reinforced with a larger number of dedicated case studies. These case studies should target Universities and colleges of different size and specialisation, in the UK and beyond. (p. 143964)

So, is ODDE good for the environment? At first glance, based on the included articles in this systematic review, we would be certainly inclined to answer this question with “yes,” especially in comparison to conventional on-campus learning and teaching. However, the studies also provided insights into certain rebound effects, where energy savings in one area are offset by increased use in another.

Herring and Roy (2002) already wrote about the effects of "dematerialization" in print-based distance education through digitization: “[…] the rapid dematerialization has been compensated for–even definitely overcompensated for–by growth in the demand for computing and communication power” (Hilty, 1999, as cited in Herring & Roy, 2002, p. 3). In the Filimonau et al. (2021) study, it was shown that savings from online learning during the COVID-19 pandemic were offset by the continued operation of the campus, even when the campus was not being used. However, this does not apply to open and distance teaching universities, which generally do not operate a large campus.

Such rebound effects are even more pronounced with new developments in educational technology that involve applications of artificial intelligence (AI). Most prominent among these are groundbreaking advances in transformer-based large language models chatbots, such as ChatGPT. Training and running generative AI applications depend on massive data processing and storage. Data centers require enormous amounts of electricity and water for cooling. It is

estimated that a search with ChatGPT uses up to five times more energy than finding the same information with a conventional search engine: “Within years, large AI systems are likely to need as much energy as entire nations” (Crawford, 2024, p. 693).

ODDE relies heavily on digital devices and infrastructure. Each year, billions of electronic devices are manufactured. The production of these devices and their batteries relies on dozens of nonrenewable resources, including scarce metals and rare earth elements. The extraction of these materials involves the excessive use of chemicals and water and the production of toxic waste, leading to pollution and deforestation (Selwyn, 2025). Vanderbauwhede (2021) points out:

> By 2040 emissions from computing alone will be more than half the emissions level acceptable to keep global warming below 1.5°C. This growth in computing emissions is unsustainable: it would make it virtually impossible to meet the emissions warming limit. (para. 1)

That being said, we have seen that ODDE can make a significant contribution to reducing the carbon footprint of HEIs; ODDE can be good for the environment, but further research on the environmental rebound effects of digital education is necessary to enable the responsible and informed selection of technologies.

Until the COVID-19 pandemic, the issue of the carbon footprint in ODDE had largely been absent from the research agenda. With the most recent publications, however, questions concerning the environmental impact of different modes of education have re-emerged. Nevertheless, on-campus education is not usually analyzed in relation to ODDE teaching operations, and the implications of open and distance education practices remain insufficiently understood in this regard. Further research is needed, particularly with regard to developing standardized procedures for measuring the carbon footprint of teaching and learning operations in higher education, as well as for examining rebound effects associated with different delivery modes.

Dedicated ODDE institutions are well represented in the studies discussed here, but they could further strengthen their profiles and positioning in the context of environmental sustainability. Meanwhile, changes in teaching and learning operations, especially delivery modes, remain largely absent from studies of campus-based education. In general, at a time of increasingly strong, selfish national tendencies, when climate change is partly ignored or even denied and many leading economies are shifting their priorities away from climate concerns, this work may feel like swimming against the tide. Nevertheless, such research is of existential importance to a sustainable future.

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*Indicates that the article is featured in the corpus of the review

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Exploring EFL Students' Use of Generative AI for Academic Writing: An Extension of UTAUT2 Model

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Abstract
Generative artificial intelligence (GenAI) has shown potential in supporting academic writing, yet limited research addressed the intention and actual use of this technology by foreign language students. To address this gap, the study employs an extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model by integrating AI self-efficacy and AI trust to investigate the factors influencing EFL students' intention and actual use of GenAI in academic writing. An online survey using a cross-sectional design involving 481 purposively selected EFL students from Indonesian universities was analyzed using partial least squares structural equation modeling (PLS-SEM) with SmartPLS 4. The results revealed that performance expectancy, effort expectancy, social influence, habit, and AI self-efficacy significantly shaped EFL students' intentions to use GenAI for academic writing, while behavioral intention, habit, and AI self-efficacy significantly influence actual use. In contrast, AI trust, facilitating conditions, and hedonic motivation show no significant effect on either intention or actual use. The model demonstrated strong explanatory power, with R^2 values of 0.806 for behavioral intention and 0.617 for actual use. The study enhances the explanatory power of UTAUT2 in GenAI-supported academic writing and offers practical insights for pedagogy and policy to promote GenAI literacy, critical evaluation skills, and responsible use in academic writing.

Keywords: Academic writing, AI self-efficacy, AI trust, EFL students, GenAI, UTAUT2

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Academic writing in a foreign language is widely recognized as a linguistically complex, cognitively demanding, and emotionally taxing task. Numerous studies have reported that students often encounter various challenges during the academic writing process. For instance, EFL students commonly encounter challenges in developing grammatical accuracy, have a limited range of vocabulary, and difficulties in achieving textual cohesion and coherence (Mustafa et al., 2022). They also face obstacles such as poor reading comprehension, brainstorming and idea generation, organizing ideas logically, developing arguments and critical thinking, selecting relevant and credible sources, writing summaries and paraphrasing, maintaining originality, and avoiding plagiarism (Altikriti, 2021; Chuenchaichon, 2022; Mustafa et al., 2022; Toprak & Yücel, 2020). Beyond linguistic and cognitive barriers, many students experience affective challenges, including anxiety, lack of motivation, and low self-confidence (Bulqiyah et al., 2021), which can lead to writing apprehension and avoidance behaviors. These challenges are intensified in online and blended learning contexts, where students may have limited access to timely, personalized feedback and instructor guidance (Gupta et al., 2022). Consequently, these issues may limit students' writing growth and reduce their engagement and performance in academic tasks.

In recent years, digital technologies have become integral to reshape how students develop academic writing and digital literacy skills. Within these environments, intelligent writing tools embedded in learning management systems (LMSs), collaborative platforms, and mobile applications provide real-time and asynchronous writing support. Among these tools, generative artificial intelligence (GenAI) represents a major pedagogical advancement. Unlike earlier writing aids restricted to grammar correction, GenAI platforms such as ChatGPT, Claude, Gemini, and Bing AI act as cognitive partners in digital classrooms, facilitating brainstorming, idea development, translation, grammatical refinement, argument structuring, and feedback generation (Abdullah, 2025; Allen & Mizumoto, 2024; Cardon et al., 2023; Malik et al., 2023; Marzuki et al., 2023; Mo & Crosthwaite, 2025; Tiandem-Adamou, 2024). By supporting students in these tasks, GenAI enables iterative writing processes, personalized feedback, and the enhancement of self-regulated learning strategies. However, its integration raises concerns about overreliance on automated assistance, diminished critical thinking, and ethical issues such as plagiarism and data privacy (Picciano, 2024; Sarwanti et al., 2024). These challenges highlight the need to understand the factors that influence EFL students' intention and actual use of GenAI in academic writing, providing guidance for its ethical and pedagogically sound integration.

Theoretical models such as the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) and its extended version, UTAUT2 (Venkatesh et al., 2012), have been widely used to study technology adoption in educational settings. While these models effectively explain technology use, their application to GenAI-supported academic writing remains limited. Previous studies (e.g., Tran, 2025; Wang, 2025; Yang, 2025) have mainly focused on technological predictors of students' adoption, paying less attention to the cognitive, psychological, and ethical factors that influence EFL students' use of GenAI in academic writing. Given that academic writing requires careful consideration of authorship, originality, and ethical issues, it is crucial to understand how students' confidence in using AI tools and their trust in AI-generated content affect their adoption decisions. To address this gap, this study extends the UTAUT2 framework by incorporating two critical psychological factors, AI self-efficacy (AIS) and AI trust (AIT), to examine EFL students' behavioral intention and actual use of GenAI in academic writing. By integrating these psychological mechanisms with

technological determinants, the proposed model offers a more comprehensive understanding of GenAI adoption in higher education writing contexts. Theoretically, the study enhances the explanatory power of UTAUT2 in the context of GenAI-supported academic writing, while practically, it provides insights for instructional strategies and policy decisions that can foster GenAI literacy, critical evaluation skills, and responsible use in academic writing.

Literature Review

GenAI in Academic Writing

Advances in GenAI are profoundly transforming academic writing, largely due to the evolution of LLMs like ChatGPT, Gemini, and Claude. These models, built on massive linguistic and multimodal datasets, are capable of producing a variety of content types, from text and images to audiovisual outputs and code, by learning and replicating patterns from their data (Feuerriegel et al., 2024). As these technologies become more sophisticated and widely available, students are progressively leveraging them to facilitate academic writing and strengthen their writing competence (Kim et al., 2025; Sarwanti et al., 2024). For instance, studies by Picciano (2024) and Tiandem-Adamou (2024) highlight GenAI's role in the early stages of writing, where it helps generate ideas, stimulate brainstorming, and organize outlines, offering a clear and structured foundation for academic work. Malik et al. (2023) further emphasize that during the drafting process, these tools offer continuous and interactive feedback that helps students expand and refine their ideas while improving language accuracy and coherence. GenAI also provides real-time suggestions on content organization, appropriate word choice, and grammar correction, significantly enhancing the clarity and overall quality of writing (Malik et al., 2023; Zimmerman, 2023). Beyond correcting basic errors, GenAI fosters the enhancement of complex writing skills, including planning, monitoring, and evaluating, empowering students to manage and take responsibility for their writing more effectively (Molenaar, 2022).

Despite its advantages, GenAI's use in academic writing presents significant challenges. Sarwanti et al. (2024) found that ChatGPT can produce misinformation if not carefully reviewed, potentially compromising the credibility of academic work. Beyond issues of accuracy, scholars have questioned the moral implications of GenAI-assisted writing, particularly regarding plagiarism and authorship (Chanpradit, 2025; Mo & Crosthwaite, 2025; Picciano, 2024). Studies further suggest that GenAI may increase instances of academic dishonesty and create inequities in access, as students with greater digital skills or resources may benefit disproportionately (Bae et al., 2024; Stahl & Eke, 2024). In addition to ethical concern, the over-reliance on GenAI tools can negatively impact students' intellectual development. This concern is echoed by Kim et al. (2025), who emphasize that such dependence may prevent students from developing core academic competencies like independent problem-solving and reflective thinking, ultimately undermining the educational value of writing tasks. While prior studies have examined the potential advantages and drawbacks of employing GenAI for academic writing, there remains a lack of in-depth empirical studies exploring the factors that shape its acceptance and usage. This gap underscores the need for theory-driven investigations to better understand how and why EFL students engage with GenAI in academic writing. Accordingly, investigating the factors that shape EFL students' behavioral intention and actual use of GenAI will not only enrich our understanding of EFL students' behavior in technology-supported writing environments, but also

support the development of targeted pedagogical frameworks that foster more effective and ethical use of GenAI in foreign language writing instruction.

UTAUT2

The study is grounded in the UTAUT2 model (Venkatesh et al., 2012). This model extends the original UTAUT introduced by Venkatesh et al. (2003), which identified four primary predictors of technology use: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), all of which influence behavioral intention (BI) and actual use (AU). UTAUT2 further incorporates three additional dimensions: hedonic motivation (HM), price value (PV), and habit (HT). These modifications significantly enhance the model's explanatory power, accounting for 74% of the variance in behavioral intention and 52% in actual use (Venkatesh et al., 2012). Despite its robustness, UTAUT2 was originally conceptualized for commercial environments, emphasizing the functional evaluation of technologies and not accounting for the cognitive and ethical judgments required when using GenAI in educational contexts.

Recent extensions of UTAUT2 in GenAI adoption show that performance expectancy is a strong predictor of students' intention to use GenAI tools like ChatGPT (Strzelecki, 2024; Faraon et al., 2025). In contrast, other studies reported that habit emerges as a strong determinant of GenAI adoption (Dietrich & Grassini, 2025; Moradi, 2025). These results suggest that GenAI adoption is shaped not only by students' belief that the tool enhances academic performance, but also by the extent to which GenAI use becomes a habitual learning behavior. However, the adoption is influenced not only by perceived usefulness and habitual use, but also by individual learning goals and personal engagement with the technology. Recent studies involving EFL students in China showed that motivation and personal innovativeness also significantly shape the intention to adopt GenAI (Zheng et al., 2024; Liu et al., 2025), indicating that students in language-focused environments use GenAI not merely to complete academic tasks but to enhance their language development.

Although recent extensions of UTAUT2 have advanced understanding of technology adoption, their application to GenAI in higher education remains limited in addressing EFL students' cognitive and ethical complexities in academic writing, which requires evaluating the accuracy, credibility, originality, and citation integrity of AI-generated writing. Because of these cognitive and ethical demands, strong performance expectancy or habitual use does not necessarily translate into the actual use of GenAI in academic writing. While students may acknowledge the advantages of GenAI, many remain hesitant when they lack the necessary skills or confidence to assess its reliability or ethically apply its outputs. As a result, the intersection of cognitive competence, ethical awareness, and technology acceptance remains insufficiently examined in extended UTAUT2 research, particularly within the domain of GenAI-assisted academic writing. These overlooked dimensions have recently emerged as key determinants in AI-supported learning, where perceived competence and trust strongly influence both intention and sustained use of intelligent technologies (Amin et al., 2025; Chu et al., 2025a; Hsiao & Tang, 2024; Hsu & Silalahi, 2024; Lin et al., 2025), thereby providing the theoretical basis for incorporating AI self-efficacy and AI trust into the present model. To address this gap, the current study extends UTAUT2 by integrating these constructs to provide a more comprehensive explanation of EFL students' intention and actual use of GenAI for academic writing. Both constructs were operationalized through validated survey measures adapted from prior

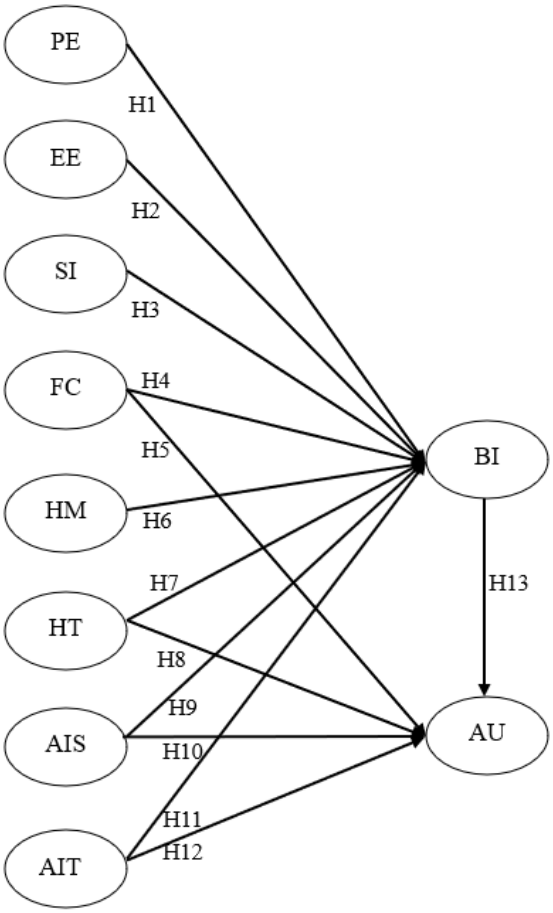
technology acceptance research to ensure conceptual alignment and measurement reliability. Given the study's aim to examine the interrelationships among multiple latent constructs, SEM was employed to test direct effect. The following section presents the research model and hypotheses developed from this integrated theoretical and methodological foundation.

Model Conceptualization and Hypothesis Development

The present extends the UTAUT2 model by adding two additional variables: AI self-efficacy and AI trust to provide a more comprehensive explanation of EFL students' intention and actual use of GenAI for academic writing. In this study, price value was excluded because it is a consumer-oriented construct and is not relevant in the higher education context, where most EFL students use GenAI tools at no cost. As illustrated in Figure 1, the resulting research framework informs the hypothesis development presented in the subsequent subsections.

Figure 1

The Proposed Model



Performance Expectancy

Venkatesh et al. (2003) describe performance expectancy as the belief that adopting a particular technology can improve one's ability to complete tasks more effectively. In this study, it refers to EFL students' perceptions that using GenAI tools can enhance their academic writing

outcomes. Recent studies have shown that that performance expectancy is one of the strongest predictors of students' intention to adopt GenAI for learning (Grassini et al., 2024; Haryanto et al., 2026; Strzelecki, 2024; Surachmi et al., 2025; Tran, 2025; Xu et al., 2025; Yang, 2025; Zheng et al., 2024). Based on this, the study formulates the following hypothesis:

H1: Performance expectancy positively influences EFL students' behavioral intention.

Effort Expectancy

According to Venkatesh et al. (2003), effort expectancy refers to an individual's perception of how effortless and uncomplicated a technology is to operate. In this study, effort expectancy refers to students' belief that operating GenAI is simple and can be done without difficulty during the academic writing process. Effort expectancy has shown that effort expectancy plays a critical role in shaping students' behavioral intention to adopt GenAI tools (Dietrich & Grassini, 2025; Haryanto et al., 2026; Tran, 2025; Strzelecki, 2024; Surachmi et al., 2025; Xu et al., 2025; Yang, 2025; Zheng et al., 2024). Therefore, the following hypothesis is formulated:

H2: Effort expectancy positively influences EFL students' behavioral intention.

Social Influence

Venkatesh et al. (2012) define social influence as the extent to which an individual's choice to use a technology is affected by the expectations or advice of those they value. In this study, it relates to how EFL students' adoption of GenAI tools for academic writing is guided by the feedback, encouragement, or endorsement of peers, and lecturers. Numerous studies have reported that social influence is a significant predictor of behavioral intention to adopt GenAI tools such as ChatGPT (Dietrich & Grassini, 2025; Haryanto et al., 2026; Liu et al., 2025; Moradi, 2025; Strzelecki, 2024; Surachmi et al., 2025; Wang, 2025; Xu et al., 2025; Yang, 2025; Zheng et al., 2024). Based on these results, the following hypothesis is proposed:

H3: Social influence positively influences EFL students' behavioral intention.

Facilitating Conditions

Facilitating conditions encompass the belief that adequate technical resources, support systems, and infrastructure are available to enable the effective use of new technologies (Venkatesh et al., 2023). In this study, facilitating conditions denote EFL students' views on having dependable internet access, proper devices, and adequate institutional or technical support to effectively utilize GenAI tools in their academic writing. Within the UTAUT2 framework, facilitating conditions are regarded as a critical determinant that influences both users' intention to use a technology and their actual usage. Recent studies confirm that facilitating conditions are significantly associated with behavioral intention and actual use of GenAI tools such as ChatGPT (Amin et al., 2025; Dietrich & Grassini, 2025; Haryanto et al., 2026; Liu et al., 2025; Moradi, 2025; Surachmi et al., 2025; Xu et al., 2025; Yang, 2025). Accordingly, the following hypotheses are proposed:

H4: Facilitating conditions positively influence EFL students' behavioral intention.

H5: Facilitating conditions positively influence EFL students' actual use.

Hedonic Motivation

Venkatesh et al. (2012) describes hedonic motivation as the level of enjoyment or excitement that encourages individuals to adopt a new technology. In this study, it refers to the positive emotional experience EFL students gain from using GenAI tools while working on their academic writing. Previous research has demonstrated that hedonic motivation is a significant predictor of technology adoption in mobile learning (Dinh et al., 2025) and in the use of GenAI tools such as ChatGPT (Haryanto et al., 2026; Strzelecki, 2024; Surachmi et al., 2025; Zheng et al., 2024). Based on these results, this study puts forward the following hypothesis:

H6: Hedonic motivation positively influences EFL students' behavioral intention.

Habit

Habit denotes the degree to which an individual's use of a technology is habitual and seamlessly integrated into daily activities (Venkatesh et al., 2012). In this study, habit refers to how routinely EFL students rely on GenAI tools as part of their academic writing process. Venkatesh et al. (2012) highlight habit as a key determinant that shapes individuals' behavioral intention and actual use of technology. Recent studies further confirmed that habit significantly influences individuals' intention to use and actual use of GenAI tools such as ChatGPT (Haryanto et al., 2026; Moradi, 2025; Surachmi et al., 2025; Zheng et al., 2024). Therefore, this study hypothesizes:

H7: Habit positively influences EFL students' behavioral intention.

H8: Habit positively influences EFL students' actual use.

AI Self-Efficacy

Self-efficacy, grounded in Social Cognitive Theory (Bandura, 1986), refers to an individual's confidence in their ability to successfully perform a task. While foundational, this construct emerged from a general psychological context and does not inherently account for situations involving digital or automated systems. To contextualize self-efficacy within technology-mediated environments, prior research introduced more domain-specific derivations such as computer self-efficacy (Compeau & Higgins, 1995), internet self-efficacy (Eastin & LaRose, 2000), and technology self-efficacy (Laver et al., 2012). These adaptations emphasize users' confidence in operating technological tools to accomplish tasks. Recent advancements in autonomous technologies further extend the construct toward AI self-efficacy, defined as an individual's confidence in their ability to interact with and effectively utilize artificial intelligence systems (Wang & Chuang, 2024). In this study, AI self-efficacy reflects EFL students' confidence in using GenAI to perform academic writing tasks. Prior studies have shown that AI self-efficacy significantly influences behavioral intention (Chu et al., 2025a, 2025b; Hsiao & Tang, 2024; Hsu & Silalahi, 2024) and also predicts actual use (Chu et al., 2025a, 2025b). Accordingly, the following hypotheses are proposed:

H9: AI self-efficacy positively influences EFL students' behavioral intention.

H10: AI self-efficacy positively influences EFL students' actual use.

AI Trust (AIT)

Trust was originally conceptualized in interpersonal relationships as an individual's willingness to accept vulnerability based on positive expectations of another person's actions (Deutsch, 1960; Mayer et al., 1995). In this interpersonal context, trust develops through evaluations of ability, benevolence, and integrity, which are inherently tied to human intentions.

As technology became involved in decision-making, the concept of trust expanded beyond human interactions and shifted to systems, forming the basis of technology trust, where users evaluate whether a system performs tasks reliably, securely, and consistently despite the absence of emotions or intentions (McKnight et al., 2002; Gefen et al., 2003). The emergence of autonomous and GenAI introduced yet another shift, requiring trust to encompass not only functional performance but also the system's decision-making qualities. Consequently, evaluations of AI systems extend beyond basic reliability to considerations of transparency, predictability, fairness and ethical conduct, and dependability. Hence, AI trust refers to an individual's belief that an AI system can be relied on to operate transparently, ethically, and responsibly even when its internal workings are not fully visible (Baroni et al., 2022). In this study, AI trust captures EFL students' confidence that GenAI tools behave reliably and ethically when supporting academic writing tasks. Recent studies report that AI trust significantly contributes to both students' intention (Amin et al., 2025; Lin et al., 2025) and actual usage behavior (Mustofa et al., 2025). Therefore, the following hypotheses are proposed:

H11: AI trust positively influences EFL students' behavioral intention.

H12: AI trust positively influences EFL students' actual use.

Behavioral Intention and Actual Use

Behavioral intention reflects an individual's motivational preparedness to carry out a particular action (Venkatesh et al., 2012), whereas actual use refers to the concrete execution of that action in practice. Within this study, behavioral intention is conceptualized as EFL students' willingness and drive to engage with GenAI tools for their academic writing assignments. In contrast, actual use captures the frequency and degree to which these students actively integrate GenAI tools into their writing activities. Following the UTAUT2 framework, behavioral intention is expected to directly influence actual use (Amin et al., 2025; Chu et al., 2025b; Grassini et al., 2024; Haryanto et al., 2026; Hsu & Silalahi, 2024; Liu et al., 2025; Strzelecki, 2024; Surachmi et al., 2025; Yang, 2025; Zheng et al., 2024). Accordingly, the study puts forward the following hypothesis:

H13: Behavioral intention positively influences EFL students' actual use.

Methods

Participants

This study recruited EFL students from academic writing courses offered at four universities in Indonesia, including two private and two public universities located in West Java and Central Java. These courses are compulsory subjects typically taken in the fourth or fifth semester within English Education programs and are designed to prepare students for writing their theses and developing scientific publications. The curriculum provides comprehensive training in academic writing structure and techniques, encompassing stages such as drafting research proposals and literature reviews, writing methodologies, presenting results, and applying proper citation styles. Through these courses, students acquire the knowledge and skills necessary to produce coherent, ethical, and publication-ready academic works that meet scholarly standards.

Participants were selected through purposive sampling, targeting those who had prior experience with GenAI and its use in academic writing. A total of 357 students participated in this study, consisting of 222 females (62.2%) and 135 males (37.8%). This gender distribution aligns with Wurisoedjatmiko (2017), who reported that language and literature studies tend to attract more female students. The participants were between 17 and 24 years old, with the majority (80.8%) aged between 21 and 24 years. In terms of years of study, 41.3% of the students were in their second year, while 58.7% were in their third year. The demographic details summarized in Table 1 provide important context for understanding the diversity and representativeness of the participants.

Table 1

Participants Demographic Information (N=375)

Characteristic	Number	Percentage
Sex		
Male	135	47.8
Female	222	62.2
Age		
17-20 years old	72	19.2
21-24 years old	303	80.8
Years of Study		
2	155	41.3
3	220	58.7
Type of Institutions		
Private universities	234	62.4
Public universities	141	37.6

Instrument

This study employed an online survey to gather data, structured in two sections. The first collected information on participants' demographics and backgrounds, while the second evaluated the ten constructs included in the proposed model. All measurement items were adapted from previously validated instruments. Items for performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, behavioral intention, and actual use were adapted from validated UTAUT2 scales developed by Venkatesh et al. (2012). Items for AI self-efficacy were adapted from Hsiao & Tang (2024) and Hsu & Silalahi (2024), while items for AI trust were adapted from Amin et al. (2025). All items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). No new items were developed, and only minor wording adjustments were made to fit the academic writing context. The full list of survey items is provided in the Appendix.

To enhance the content validity of the instrument, the questionnaire underwent a review process by two experts specializing in educational technology and English language teaching who have research experience in AI-assisted learning and the use of ChatGPT in academic contexts. They evaluated each item for clarity, relevance, and alignment with the theoretical constructs and research objectives. Minor revisions were made based on their feedback, particularly in terms of wording precision and clarity. Following the expert validation, a pilot test

was administered to 40 undergraduate EFL students (aged 18–24) to evaluate item comprehensibility, the interpretation of statements, and the technical functionality of the Google Forms platform. The participants consisted of 28 females and 12 males from the same four Indonesian universities that later participated in the main data collection. The pilot results confirmed the reliability and validity of all variables, including discriminant validity (Hair et al., 2022). Internal consistency was satisfactory, with Cronbach's alpha values above 0.70 for every construct. To broaden accessibility, the final questionnaire was distributed online in both Indonesian and English. A back-translation procedure was adopted to ensure equivalence between the two language versions: The English version was first translated into Indonesian by a bilingual specialist, after which a second independent translator rendered it back into English. The back-translated version was compared with the original, and any inconsistencies in meaning or terminology were revised until both versions were conceptually aligned (Tyupa, 2011).

Data Collection

An online questionnaire was developed using Google Forms and distributed via WhatsApp, a widely used communication platform among Indonesian students. To expand the reach, four lecturers from two private and public universities in West Java and Central Java assisted in sharing the survey link with their EFL students and encouraging participation. The survey was administered from March to April 2025, and the questionnaire required approximately seven minutes to complete. The survey remained open for one month, yielding 375 responses.

Data Analysis

Prior to the main analysis, the study assessed potential common method bias (CMB) to ensure that the data collection process did not distort the relationships among variables. This assessment involved checking variance inflation factor (VIF) values using SmartPLS 4. All inner VIF values were found to be below the recommended cutoff of 3.3, indicating that CMB was not a major concern. After confirming this, the study employed PLS-SEM using SmartPLS 4. The analytical process was carried out in two main stages. The first stage involved assessing the measurement model to ensure that all constructs met the criteria for reliability and validity. Once the measurement model was confirmed, the second stage evaluated the structural model to test the hypothesized paths and determine the strength and significance of the relationships between constructs.

Results

Common Method Bias

Data for this study were obtained through self-reported questionnaires, which carry a potential risk of common method bias (CMB) due to the use of a single source. To check for CMB, the study followed Kock's (2015) recommendation of applying a full collinearity test with the Variance Inflation Factor (VIF), where values below 3.3 suggest that CMB is not a major issue. As shown in Table 2, all VIF values ranged between 1.046 and 2.842, remaining under the acceptable threshold. These results indicate that CMB is unlikely to be a significant issue in this study.

Table 2

Collinearity Test (VIF)

	BI	AU
PE	1.726	
EE	1.046	
SI	1.177	
FC	1.094	1.079
HM	2.842	
HT	2.514	1.596
AIS	1.267	1.322
AIT	1.040	1.035
BI		1.587
AU		

Note: PE: Performance Expectancy, EE: Effort Expectancy, SI: Social Influence, FC: Facilitating Conditions, HM: Hedonic Motivation, HT: Habit, AIS: AI Self-Efficacy, AIT: AI Trust, BI: Behavioral Intention, AU: Actual Use

Measurement Model

The reliability and validity of the constructs were confirmed through a detailed assessment of the measurement model. Initially, the PLS-SEM algorithm was used to calculate factor loadings, all of which were above 0.70, indicating that the items accurately reflected their associated latent variables. Next, reliability was evaluated using Cronbach's Alpha and Composite Reliability (CR). As shown in Table 3, every construct exceeded the 0.70 threshold for both measures, demonstrating strong internal consistency. Convergent validity was established by calculating the Average Variance Extracted (AVE), with all constructs scoring above 0.50, which implies that they captured a substantial amount of variance from their respective indicators.

Table 3

Measurement Model

Variables	Item	Factor Loading	Cronbach's Alpha	CR	AVE
PE	PE1	0.904	0.913	0.939	0.793
	PE2	0.886			
	PE3	0.895			
	PE4	0.878			
EE	EE1	0.881	0.912	0.938	0.790
	EE2	0.897			
	EE3	0.873			
	EE4	0.904			
SI	SI1	0.868	0.895	0.927	0.760
	SI2	0.874			
	SI3	0.868			
	SI4	0.877			
FC	FC1	0.893	0.893	0.933	0.823
	FC2	0.905			

	FC3	0.923			
HM	HM1	0.918	0.894	0.934	0.825
	HM2	0.920			
	HM3	0.886			
HT	HT1	0.845	0.881	0.918	0.737
	HT2	0.862			
	HT3	0.861			
	HT4	0.867			
AIS	AIS1	0.823	0.842	0.894	0.678
	AIS2	0.802			
	AIS3	0.841			
	AIS4	0.827			
AIT	AIT1	0.793	0.904	0.916	0.731
	AIT2	0.804			
	AIT3	0.894			
	AIT4	0.923			
BI	BI1	0.876	0.910	0.937	0.788
	BI2	0.895			
	BI3	0.876			
	BI4	0.903			
AU	AU1	0.872	0.901	0.931	0.771
	AU2	0.890			
	AU3	0.875			
	AU4	0.876			

To ensure the robustness of the measurement model, discriminant validity was evaluated through both the Heterotrait-Monotrait (HTMT) ratio and the Fornell–Larcker criterion. Based on the guidelines of Henseler et al. (2015), HTMT values below 0.90 suggest that constructs are sufficiently distinct. As indicated in Table 4, the HTMT values in this study ranged from 0.057 to 0.846, all well below the recommended threshold, signifying clear differentiation among the constructs. Furthermore, the Fornell–Larcker approach stipulates that the square root of each construct's AVE must surpass its correlations with any other construct. Table 5 shows that this requirement was met, with AVE square roots between 0.824 and 0.954, all exceeding the respective inter-construct correlations. These results confirm that the model achieves acceptable reliability, convergent validity, and discriminant validity, thereby providing a strong basis for proceeding with the structural model analysis.

Table 4

Discriminant Validity Based on HTMT

	PE	EE	SI	FC	HM	HT	AIS	AIT	BI	AU
PE										
EE	0.107									
SI	0.307	0.159								
FC	0.083	0.055	0.162							

HM	0.694	0.098	0.247	0.148						
HT	0.512	0.178	0.296	0.217	0.827					
AIS	0.317	0.075	0.292	0.067	0.347	0.459				
AIT	0.062	0.060	0.053	0.075	0.094	0.152	0.121			
BI	0.744	0.326	0.528	0.124	0.625	0.622	0.500	0.072		
AU	0.490	0.198	0.481	0.097	0.535	0.583	0.529	0.037	0.741	

Table 5

Discriminant Validity Based on Fornell-Lacker Criterion

	PE	EE	SI	FC	HM	HT	AIS	AIT	BI	AU
PE	**0.891**									
EE	0.101	**0.889**								
SI	0.280	0.147	**0.872**							
FC	0.076	0.050	0.146	**0.907**						
HM	0.627	0.091	0.222	0.131	**0.909**					
HT	0.461	0.163	0.264	0.195	0.734	**0.859**				
AIS	0.279	0.063	0.255	-0.054	0.302	0.395	**0.824**			
AIT	0.069	0.058	-0.012	-0.092	0.076	0.135	0.087	**0.855**		
BI	0.679	0.304	0.478	0.111	0.564	0.558	0.439	0.069	**0.887**	
AU	0.444	0.180	0.435	0.088	0.481	0.521	0.464	0.042	0.672	**0.878**

Note: The bold values represent the square root of AVE

Structural Model

Following the validation of the robust measurement model, the structural model was evaluated using bootstrapping with 5,000 resamples. To evaluate the explanatory power of the structural model, the coefficient of determination (R2) was assessed for each endogenous construct. According to Hair (2022), R^2 values may be classified as strong (0.75), moderate (0.50), or weak (0.25), depending on the degree of variance explained. As presented in Figure 2, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit collectively produced an R^2 value of 0.659 for behavioral intention, indicating moderate to strong explanatory power. Furthermore, actual use achieved an R^2 value of 0.508, explained by behavioral intention, AI self-efficacy, habit, facilitating conditions, and AI trust, reflecting a moderate level of predictive accuracy. The results indicate that the extended UTAUT2 model provides a solid explanation of students' intentions to use GenAI and their subsequent actual use, with stronger predictive power for behavioral intention.

According to the PLS-SEM analysis shown in Table 6, eight of the thirteen hypotheses were statistically supported, while the remaining five were not. Performance expectancy (β = 0.445, $p < 0.001$), effort expectancy ($\beta = 0.184$, $p < 0.001$), social influence ($\beta = 0.229$, $p < 0.001$), habit ($\beta = 0.160$, $p = 0.006$), and AI self-efficacy ($\beta = 0.167$, $p < 0.001$) exerted significant positive effects on behavioral intention, confirming H1, H2, H3, H7, and H9. Among these predictors, performance expectancy demonstrated the strongest influence, indicating that students' decisions to adopt GenAI are shaped primarily by perceived academic benefits rather than usability factors or social pressure.

For actual use, habit ($\beta = 0.176$, $p < 0.001$), AI self-efficacy ($\beta = 0.179$, $p < 0.001$), and behavioral intention ($\beta = 0.497$, $p < 0.001$) significantly influenced students' use of GenAI, supporting H8, H10, and H13. Behavioral intention emerged as the strongest predictor of actual use, implying that once students form the intention to use the technology, that intention becomes the main driver of their actual engagement with GenAI.

In contrast, facilitating conditions did not significantly influence either behavioral intention ($\beta = 0.006$, $p = 0.867$) or actual use ($\beta = 0.005$, $p = 0.888$). Hedonic motivation also had no significant effect on behavioral intention ($\beta = 0.050$, $p = 0.390$). Likewise, AI trust did not significantly predict behavioral intention ($\beta = -0.009$, $p = 0.813$) or actual use ($\beta = -0.031$, $p = 0.472$). Thus, H4, H5, H6, H11, and H12 were rejected. These non-significant findings suggest that students' adoption of GenAI is driven more by its functional academic value than by enjoyment, institutional support, or trust in the technology.

The effect size (f^2) for each independent variable in the structural model offers valuable insight into the magnitude of its influence. According to Hair et al. (2022), f^2 values of 0.02, 0.15, and 0.35 correspond to small, medium, and large effects, respectively. Sarstedt et al. (2022) further explain that f^2 values below 0.02 are considered negligible. As shown in Table 6, the analysis found that performance expectancy had a large effect on behavioral intention, followed by behavioral intention on actual use. Smaller effects were observed for social influence on behavioral intention, effort expectancy on behavioral intention, habit on behavioral intention and actual use, and AI self-efficacy on both behavioral intention and actual use. In contrast, facilitating conditions, hedonic motivation, and AI trust had negligible effect sizes, indicating minimal influence on behavioral intention and actual use.

Figure 2

Results of the Proposed Extended UTAUT2 Model

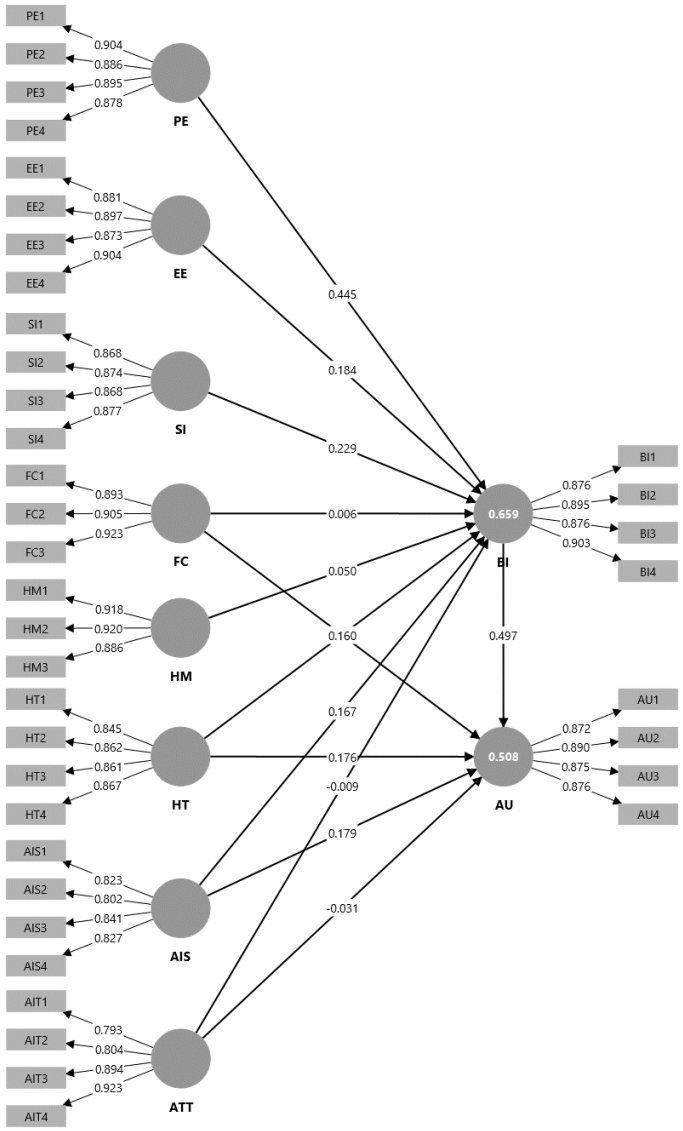


Table 6

Structural Model Results

Hypothesis	Relationship	Path	*t*-values	*p*-values	f^2	Decision
H1	PE → BI	0.445	10.203	0.000	0.335	Yes
H2	EE → BI	0.184	5.516	0.000	0.095	Yes
H3	SI → BI	0.229	6.792	0.000	0.131	Yes

H4	FC → BI	0.006	0.168	0.867	0.000	No
H5	FC → AU	0.005	0.140	0.888	0.000	No
H6	HM → BI	0.050	0.860	0.390	0.003	No
H7	HT → BI	0.160	2.733	0.006	0.030	Yes
H8	HT → AU	0.176	3.657	0.000	0.039	Yes
H9	AIS → BI	0.167	4.562	0.000	0.065	Yes
H10	AIS → AU	0.179	4.263	0.000	0.049	Yes
H11	AIT → BI	-0.009	0.236	0.813	0.000	No
H12	AIT → AU	-0.031	0.719	0.472	0.002	No
H13	BI → AU	0.497	10.234	0.000	0.316	Yes

Discussion

This study extends the UTAUT2 framework by integrating AI self-efficacy and AI trust to explain EFL students' behavioral intention and actual use of GenAI for academic writing. The extended model demonstrates strong explanatory power, accounting for 80.6% of the variance in behavioral intention and 61.7% in actual use. This study extends UTAUT2 by demonstrating that in academic writing contexts, AI self-efficacy predicts both intention and actual use, whereas AI trust loses predictive power when usage is task-oriented and low-risk. The extended UTAUT2 model proves theoretically robust in the GenAI–academic writing context. This indicates that students' decisions to adopt GenAI are driven more by perceived capability and performance benefits than by trust in the system. Thus, this study not only validates UTAUT2 but also refines it for academic writing contexts in which users can control and revise GenAI output.

Performance expectancy emerged as the strongest predictor of behavioral intention. This result is in line with Grassini et al. (2024), Tran (2025), Xu et al. (2025), and Zheng et al. (2024), who reported that performance expectancy is the most influential factor in students' adoption of GenAI, as students are more willing to adopt GenAI tools when they believe that the technology can enhance their learning outcomes. The strong effect of performance in this study indicates that EFL students choose to use GenAI tools such as ChatGPT because they believe it can improve their academic writing performance. Consistent with this, Wang (2025) found that Chinese EFL learners are more likely to use large language models (LLMs) such as ChatGPT when they perceive that these tools can improve the quality, clarity, and efficiency of their academic writing. Yang (2025) further confirms that performance expectancy is the primary factor driving students to adopt GenAI because they believe the technology helps them complete writing tasks more efficiently. Similarly, Strzelecki (2024) reported that performance expectancy is the strongest determinant of students' intention to use ChatGPT, as they prioritize its functional benefits such as increased efficiency, improved output quality, and academic support when deciding to adopt the technology.

Behavioral intention also emerged as a strong predictor of actual use for GenAI tools among EFL students, consistent with previous studies (Grassini et al., 2024; Hsu & Silalahi, 2024; Liu et al., 2025; Zheng et al., 2024). Supporting this, Wang (2025) reported that Chinese EFL learners with strong intentions and favorable attitudes toward large language models (LLMs) such as ChatGPT consistently apply the technology in their academic writing activities. Yang (2025) further explained that the translation of intention into actual use is primarily driven

by internal motivation, which develops when students perceive the technology as useful, easy to use, and reinforced by social encouragement. In line with this, Amin et al. (2025) confirmed that positive perceptions of ChatGPT strengthen behavioral intention, which subsequently increases the actual use of the technology in learning tasks. However, Moradi (2025) noted that the influence of behavioral intention may decrease once ChatGPT use becomes habitual and supported by sufficient facilities, as students begin using the tool automatically without needing to form a conscious intention.

The effect of social influence on behavioral intention was also statistically significant to adopt GenAI for academic writing. This result indicates that recommendations from peers, social media, and lecturers play a role in shaping EFL students' willingness to adopt GenAI in their academic writing tasks. This is consistent with Amin et al. (2025), who reported that in collectivist cultures such as Bangladesh, encouragement from peers, family members, lecturers, or classmates increases students' intention to adopt ChatGPT in higher education. However, the effect was small because social recommendations only encouraged students to try GenAI initially, while their intention to continue using it was driven more by personal academic needs, the benefits they experienced, and their individual writing preferences rather than by ongoing external influence. Yang (2025) supports this by explaining that social support typically functions only as an initial trigger through internalization, whereas continued usage is shaped by personal needs and beliefs. Strzelecki (2024) further shows that early GenAI adopters, particularly those with higher digital literacy, depend more on personal initiative than on external expectations. Thus, while social influence may encourage initial experimentation, sustained adoption of GenAI for academic writing is largely guided by self-directed academic goals rather than external encouragement.

Effort expectancy was also a significant positive predictor of behavioral intention, though with a relatively smaller effect size. This may be because EFL students involved in academia writing are already accustomed to working with digital tools and are highly adaptable to new technologies. Consequently, using GenAI requires little effort or learning time, which reduces the importance of perceived ease of use in shaping their decision to adopt the technology. This is supported by Yang (2025), who highlights that students tend to adopt GenAI when they believe that the technology does not require extensive learning effort and can streamline academic tasks efficiently. Likewise, Strzelecki (2024) found that GenAI like ChatGPT is generally viewed as easy and practical to use, which further lowers technical barriers and encourages adoption. However, this result contrasts with Amin et al. (2025), who reported that effort expectancy does not significantly influence students' behavioral intention because students who are not familiar with advanced AI tools such as ChatGPT tend to prioritize academic credibility and perceived performance benefits over ease of use. Likewise, Moradi (2025) found that university EFL learners no longer consider ease of use in their decision to adopt GenAI because these digital tools have already become part of their daily routines, rendering effort expectancy irrelevant in their decision-making process. These inconsistencies suggest that GenAI adoption in academic writing is more utilitarian than hedonic, and trust becomes secondary when students retain full control over revision and editing.

AI self-efficacy showed a statistically significant effect on both behavioral intention and actual use, but with a small impact on EFL students' intention to use GenAI for academic

writing. This result aligns with Chu et al. (2025a, 2025b), who explain that students who believe they are capable of operating a learning technology tend to form the intention to use it, which subsequently translates into actual use. Consistent with this, Hsiao and Tang (2024) observed that higher levels of self-efficacy encourage students to engage with GenAI without fear of making mistakes, thereby strengthening their intention to continue using it. Chen et al. (2024) further reported that AI self-efficacy significantly influences actual use, as confidence in interacting with AI creates a sense of control and motivates sustained engagement in learning tasks. However, although students generally feel capable of using GenAI, their decisions to apply it in academic writing are constrained by lecturer expectations and institutional policies. In the Indonesian context, GenAI use is often permitted but subject to strict conditions, such as maintaining AI-generated text below a specified detection threshold (e.g., 20%), which leads students to limit GenAI to supplementary functions, such as idea generation or language refinement, rather than relying on it for full task completion. This cautious adoption pattern reflects students' efforts to benefit from GenAI while simultaneously complying with academic integrity requirements.

Habit was found to have a significant but weak effect on both behavioral intention and actual use of GenAI for academic writing. This result is consistent with Zhao et al. (2025), who reported that habit influences both intention and usage because repeated engagement with a technology increases users' familiarity and comfort, which in turn encourages continued use. Moradi (2025) further adds that when a behavior becomes habitual, students tend to use GenAI automatically without requiring deliberate intention or conscious decision-making. The weak effect observed in this study suggests that although some EFL students have begun using GenAI tools such as ChatGPT, these tools have not yet become a regular or automatic component of their academic writing routine. Instead, students tend to rely on GenAI only when facing specific academic demands, such as meeting deadlines, overcoming writer's block, or resolving language-related difficulties. This differs from earlier studies that identified habit as a strong predictor of ChatGPT use (Grassini et al., 2024; Dietrich & Grassini, 2025), indicating that habitual use becomes dominant only when the technology is fully integrated into users' daily workflow.

Interestingly, hedonic motivation showed a negligible, non-significant effect on behavioral intention. Moradi (2025) similarly observed that hedonic motivation does not influence behavioral intention because students do not use GenAI for enjoyment; instead, they rely on it to accomplish academic writing tasks that require precision, productivity, and compliance with lecturers' expectations and institutional regulations. This result contradicts several prior studies on technology adoption (Dinh et al., 2025; Strzelecki, 2024), which reported significant positive relationships between hedonic motivation and behavioral intention. The non-significant effect of hedonic motivation on behavioral intention in this study is likely due to the utilitarian nature of GenAI use. Indonesian EFL students interact with the technology primarily to accomplish academic writing tasks within limited time frames. Under such goal-driven conditions, emotional enjoyment is less relevant, and students focus more on the performance advantages the tool provides rather than on its entertainment value.

Unlike earlier studies that emphasized AI trust as a key predictor of technology adoption (Lin et al, 2025; Mustofa et al., 20255), this study found that AI trust did not have a direct and

significant effect on EFL students' behavioral intention and actual use of GenAI in academic writing. This result differs from Amin et al. (2025), who reported that trust significantly influences intention, where students who strongly believe in ChatGPT's reliability are more inclined to adopt it, and such trust acts as a mediating factor linking perceived usefulness, ease of use, and social influence to their intention. A plausible explanation for the insignificant effect of AI trust in this study is that EFL students prioritize task efficiency and the quality of their academic output rather than considerations of system reliability or ethical transparency. The use of GenAI tools for academic writing is self-directed and low risk, allowing students to freely revise or discard the generated text at any time. Because most students rely on free and accessible versions like ChatGPT, they focus more on the immediate benefits such as speed, reduced writing effort, and improved clarity than on developing a deep sense of trust toward the system. In this context, perceived performance benefits outweigh the role of trust in shaping intention or actual use.

Facilitating conditions also showed negligible, non-significant effect on behavioral intention and actual use, consistent with prior studies reporting similarly non-significant relationships with behavioral intention (Dinh et al., 2025; Grassini et al., 2024; Liu et al., 2025; Moradi, 2025; Strzelecki, 2024; Zheng et al., 2024) and actual use (Dietrich & Grassini, 2025; Zheng et al., 2024; Wang, 2025). This inconsistency may be explained by the digital autonomy of Indonesian EFL students, who already possess the necessary devices and are capable of independently accessing GenAI tools like ChatGPT. Given the wide availability, user-friendly design, and minimal learning curve of such tools, EFL students rarely depend on institutional support. As a result, external support structures become less relevant, diminishing the role of facilitating conditions in shaping their behavioral intention and actual use. In contrast, Yang (2025) demonstrated that facilitating conditions have a significant effect on actual use in GenAI-assisted second language writing, indicating that sufficient access to resources and technical support directly increases students' frequency of using GenAI. Likewise, Amin et al. (2025) reported that in developing countries, students with sufficient technological infrastructure, including reliable internet, smartphones, and personal computers, and who feel supported in using ChatGPT, are more willing to adopt and incorporate the technology into their academic routines.

Limitations

Although this study contributes valuable insights into the use of GenAI in EFL education, certain limitations should be acknowledged. First, the study adopted a cross-sectional design, collecting data at a single point in time, which limits the ability to infer causality or examine how students' engagement with GenAI tools may evolve over time. Future studies should consider longitudinal or experimental designs to capture changes in GenAI use. Second, the data were obtained through self-reported questionnaires, which may introduce response bias due to subjective perceptions and social desirability. To enhance data validity, future studies are encouraged to incorporate mixed-methods approaches to capture richer and more nuanced student experiences. Third, although this extended UTAUT2 model explains GenAI adoption effectively, the study did not examine moderating variables such as age, gender, or digital literacy. Previous research suggests that these factors may influence technology acceptance (Venkatesh et al., 2012). Including these moderators in future models may provide a deeper understanding of differences across user groups and inform more targeted pedagogical strategies. Finally, the sample was taken from only two provinces in Indonesia (Central Java and West

Java), which may limit the representativeness of the findings, as factors influencing GenAI use can vary across regions with different cultural, technological, and educational conditions. Nonetheless, the results are expected to offer meaningful insights for regions or institutions with similar characteristics in promoting the responsible and ethical use of GenAI in academic writing. Future studies should involve larger and more diverse samples, including cross-regional or cross-cultural comparisons, to better understand how contextual factors influence GenAI adoption in education.

Theoretical and Practical Implications

Building on these theoretical insights, the findings also offer important implications for education, professional practice, and institutional policy regarding the integration of GenAI tools into academic writing. In educational settings, because AI self-efficacy significantly influences both intention and actual use, lecturers should not only introduce the tool but also integrate guided, hands-on activities into online or blended formats that allow students to practice using GenAI to support academic writing. These activities can include developing outlines, refining drafts, paraphrasing text, and improving coherence, allowing students to practice applying GenAI to support academic writing. Incorporating formative feedback cycles, such as comparing AI-assisted drafts with student-written versions, encourages critical evaluation, prevents overreliance, and helps students understand when and how GenAI can effectively support learning. This approach enables students to view GenAI as a cognitive partner rather than a replacement for independent thinking, building confidence, critical thinking skills, and AI self-efficacy. By embedding these strategies, the study not only extends UTAUT2 but also provides contextual refinements for the pedagogical use of GenAI in academic writing.

The results also suggest implications for professional practice. The non-significant effect of AI trust indicates that increasing confidence and competence matters more than persuading students to trust the technology. Lecturers should therefore focus on teaching practical skills such as crafting effective prompts, evaluating the accuracy and credibility of AI-generated suggestions, and applying academic writing conventions when integrating GenAI output. Demonstrating responsible use in teaching, such as acknowledging when GenAI was used or showing how to verify sources, helps students internalize ethical and critical use of AI. These strategies ensure that students develop disciplined engagement with GenAI, using it to strengthen their academic reasoning rather than substitute for it.

Finally, at the institutional policy level, the results suggest that confidence and perceived usefulness drive adoption more strongly than trust. Thus, universities should provide clear and actionable guidelines for ethical GenAI use rather than focus solely on promoting the technology. Policies should clearly define permissible uses of GenAI, expectations for acknowledging AI contributions, and any AI-detection limits set by the institution. To support these policies, institutions can offer capacity-building programs such as AI literacy workshops or writing center support to ensure that students and lecturers are adequately prepared to use GenAI responsibly. By aligning governance with skill development, institutions can encourage responsible, ethical, and effective adoption of GenAI in academic writing.

Conclusion

This study enhances understanding of GenAI adoption in academic writing by extending the UTAUT2 model with AI self-efficacy and AI trust. The results demonstrate that AI self-efficacy significantly predicts both behavioral intention and actual use, whereas AI trust becomes less influential when students retain control over revising GenAI output. This provides a theoretical contribution by showing that, in EFL academic writing contexts, technology acceptance is driven more by capability and performance benefits than by trust in the system. Pedagogically, the results provide practical guidance for teachers and institutions: rather than encouraging students to trust GenAI, instructional efforts should focus on building AI literacy, strengthening students' ability to evaluate AI output, and supporting responsible and ethical use. Future research may apply the model in different cultural or educational settings, use qualitative approaches to explore students' reasoning and ethical concerns, and conduct longitudinal studies to understand how GenAI use evolves over time. As GenAI becomes increasingly embedded in academic writing, maintaining a balance between leveraging its benefits and ensuring responsible use will be essential to support learning without undermining students' critical thinking and writing skills.

Declarations

Disclosure Statement

The authors declare that there are no potential conflicts of interest related to this study.

Ethics Approval

Ethical approval for this study was obtained from the Research Ethics Committee of Universitas Negeri Yogyakarta. The committee reviewed and approved all research procedures, including participant recruitment, informed consent, data handling, and confidentiality protection, ensuring compliance with institutional and international ethical standards for research involving human participants. Participation was entirely voluntary. Before completing the survey, participants were informed about the study's purpose, their right to withdraw at any time without penalty, and how their data would be used. Informed consent was obtained electronically at the beginning of the questionnaire. No personal identifiable information (e.g., name, email address, student ID) was collected, and all responses were anonymized and stored securely.

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Appendix

Final set of questionnaire items based on the extended UTAUT2 Model

Construct	**Item**	
Performance Expectancy (PE)	PE1	GenAI tools are beneficial for improving my academic writing quality.
	PE2	Using GenAI enables me to complete academic writing tasks more quickly.
	PE3	GenAI increases my productivity when working on academic writing activities.
	PE4	Using GenAI improves my chances of achieving higher grades on academic writing assignments.
Effort Expectancy (EE)	EE1	Interacting with GenAI tools is clear and easy to understand.
	EE2	I am confident in operating GenAI tools for academic writing.
	EE3	Learning to use GenAI tools is easy for me.
	EE4	I find it easy to get GenAI tools to produce the outputs I need for academic writing.
Social Influence (SI)	SI1	My lecturers and peers encourage me to use GenAI for academic writing.
	SI2	People I interact with regularly believe I should use GenAI tools for academic writing tasks.
	SI3	Students who are more experienced than me are supportive and offer guidance on using GenAI tools for academic writing.
	SI4	My university provides support or promotes the use of GenAI in academic work
Facilitating Conditions (FC)	FC1	I have access to the necessary resources (internet, device, etc.) to use GenAI.
	FC2	I possess the knowledge and skills required to use GenAI effectively.
	FC3	Help is available when I encounter difficulties while using GenAI tools.
Hedonic Motivation (HM)	HM1	I find using GenAI tools for my academic writing is fun.
	HM2	Using GenAI tools gives me a pleasant and satisfying experience during academic writing activities.
	HM3	I find GenAI tools for my academic writing is entertaining.
Habit (HT)	HT1	Using Gen AI tools for academic writing has become part of my routine.

	HT2	I frequently rely on GenAI tools when working on academic writing tasks.
	HT3	I must use GenAI tools for my academic writing.
	HT4	Using GenAI tools has become natural for my academic writing tasks.
AI Self-Efficacy (AIS)	AIS1	I am confident that I have the necessary skills to use GenAI tools for academic writing.
	AIS2	I can use GenAI tools for academic writing even if no one is available to guide me.
	AIS3	I can use GenAI tools for academic writing as long as I can contact someone for help when needed.
	AIS4	I am confident that I can effectively apply GenAI tools' output to improve my academic writing.
AI Trust (AIT)	AIT1	I trust GenAI tools to provide accurate and consistent information that supports my academic
	AIT2	I believe GenAI tools are capable of giving useful guidance for academic writing tasks.
	AIT3	GenAI tools provide information in a clear and transparent manner, allowing me to understand how the output is generated.
	AIT4	I trust that GenAI tools provide information honestly and acts with integrity when supporting my academic writing.
Behavioral Intention (BI)	BI1	I plan to continue using GenAI tools for my academic writing in the future.
	BI2	I expect that I will continue using GenAI tools in my academic writing activities.
	BI3	I intend to use GenAI in the future.
	BI4	I would encourage my friends to use GenAI tools for academic writing.
Actual Use (AU)	AU1	I consider myself a regular user of GenAI tools.
	AU2	When available, I prefer to use GenAI.
	AU3	I complete most of my academic writing activities with the support of GenAI tools.
	AU4	Whenever possible, I choose to use GenAI when working on academic writing tasks.

The Role of Schemata in the Information Systems Success Model in Bridging Online Learning Equity

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Abstract
Initial cognitive structures (schemata) play a crucial role in the success of Information Systems (IS) in online learning environments, particularly in efforts to support conditions associated with learning equity. However, the IS Success Model has yet to define the role of schemata clearly. This study investigates the influence and position of schemata within the DeLone and McLean framework in the context of online learning equity, with the focus on system-related benefits that may support equitable learning conditions. While learning equity is not measured directly, the model examines perceived benefits, such as accessibility, flexibility, and participation, that are theoretically linked to fair learning opportunities. Data were collected via questionnaires administered to 252 students from two state universities, all of whom had at least one year of online learning experience. The instrument was based on the IS Success Model, which includes system quality, information quality, service quality, intention to use, user satisfaction, net benefits, and schemata. Structural Equation Modeling (SEM) was used to analyze the model. The findings show that key components of the IS Success Model are positively and significantly related to perceived system-related benefits associated with conditions that may support equitable online learning, with schemata functioning as a moderating variable. It is suggested that IS implementations should incorporate support strategies such as scaffolding, personalized guidance, and introductory content to enhance the positive impact of schemata.

Keywords: Schemata theory; online learning; IS Success Model; learning equity; quality education

Rahmi, U., & Azrul, A. (2026). The role of schemata in the information systems success model in bridging online learning equity. *Online Learning, 30*(3), 156–183. https://doi.org/10.24059/olj.v30i3.5294

The transformation of online learning has emerged as a key solution in the educational process and it continues to evolve. It offers opportunities to deliver instructional content more flexibly and broadly through digital media (Chen et al., 2022; Roddy et al., 2017). Today, most universities have adopted online learning in some form. However, research on its implementation reveals considerable variation in student experiences. While some students actively engage and report meaningful learning experiences (Cole et al., 2021), others express concerns about limited interaction among students and between students and lecturers (Chaku et al., 2021). These contrasting experiences influence student satisfaction and their intention to continue and complete courses on online learning platforms. As online learning becomes a permanent component of higher education rather than an emergency response, understanding not only whether systems function effectively, but also for whom and under what cognitive conditions they generate meaningful benefits, has become an increasingly urgent scholarly concern. In this context, it is essential to assess and ensure the quality and success of online learning systems.

Against this backdrop, the Information Systems (IS) Success Model developed by DeLone and McLean (2003) serves as a suitable framework for evaluating how online learning systems support educational goals. The model provides a comprehensive approach to system evaluation by focusing on system quality, information quality, service quality, intention to use, user satisfaction, and net benefits. In this study, the system under review is a Learning Management System (LMS), which supports both fully online and blended learning formats. This focus aligns with previous research positioning LMSs as integral to blended learning environments (Rahmi & Azrul, 2022). Nevertheless, the DeLone and McLean model does not fully capture the influence of other underlying factors that may indirectly affect learning outcomes (Lutfi, 2023).

Findings from an internal, exploratory review conducted over six semesters prior to the present study suggested that, despite occasional technical issues, students generally reported satisfaction with online learning implementation. This preliminary review was descriptive in nature and aimed to identify recurring patterns in students' experiences with online learning systems over time. Thus, these data were not included in the empirical analysis reported in this study and did not form part of the dataset used for model testing. Instead, the insights gained from this exploratory review served to motivate the present research by highlighting the need to better understand how system qualities translate into perceived benefits under varying cognitive conditions. Notably, satisfaction with system quality and the information provided plays a significant role in determining whether students comprehend learning materials (Li & Zhu, 2022). Students' perceptions of usefulness and ease of use directly shape their attitudes toward using these systems (Malureanu et al., 2021). Overall satisfaction with the learning process, including content and instructor performance, has an indirect but important impact on achieving learning outcomes (Duke, 2002; James, 2021). However, due to the diverse backgrounds of students, the benefits gained from LMS usage vary, leading to disparities in online learning implementation, which raises concerns related to online learning equity. As highlighted by UNESCO and the Sustainable Development Goals (SDGs) (UNESCO, 2016), achieving learning equity is a critical first step toward ensuring quality education.

In this study, learning equity serves as a guiding conceptual framework rather than a directly measured outcome. While equity is commonly defined as fairness, adequacy of support, and the reduction of learning barriers, the present research does not operationalize equity as an

independent construct. Rather, it examines students' perceived benefits, such as accessibility, flexibility, and accommodation of learning needs, that prior literature identifies as enabling conditions for equitable learning environments. As a result, equity is addressed indirectly through these perceived benefits rather than through explicit indicators of fairness or disadvantage.

Learning equity refers to a condition in which every student has access to learning opportunities, resources, support, and experiences that enable them to achieve their optimal academic potential. This perspective aligns with Becher et al. (2025), who emphasize that "equitable access" extends beyond devices or internet connectivity to include students' broader socio-physical contexts. These contextual factors, in turn, shape students' schemata. Another research by Miller et al. (2023) also argues that when lecturers or faculty members fail to consider students' prior experiences (which form the basis of their schemata), equitable learning cannot be fully achieved in online environments. This further highlights the central role of acknowledging learners' diverse backgrounds and experiences in designing equitable instruction.

However, while sociocultural and structural equity frameworks emphasize broader institutional, economic, and policy-level factors, the present study focuses on system-level and cognitive mechanisms through which learners experience online learning environments. This approach complements, rather than replaces, macro-level equity perspectives by examining how institutional systems translate into learner-perceived benefits.

The significance of schemata has also been acknowledged in prior literature. Each student possesses unique cognitive frameworks (schemata), which influence how they interpret and retain information, resulting in varied learning outcomes (Fuchs et al., 2021). Beyond their role as learners, students also operate within online learning environments, bringing the same underlying schemata to their interactions with system features and functions. Schemata are cognitive structures that shape how users process information and interact with systems (Chalmers, 2003; Wei et al., 2023). When users engage with a system, their existing schemata can be activated, allowing them to recognize familiar patterns and anticipate functions more efficiently. New information is then integrated either through assimilation, when it aligns with existing schemata, or through accommodation, when adjustments are required to make sense of unfamiliar features or interactions. This dynamic process not only influences users' cognitive engagement but may also shape how learners experience fairness-related aspects of system interaction.

According to major cognitive learning theories, schemata play a foundational role in learning and information processing. Piaget explains that schemata develop through assimilation and accommodation, allowing learners to integrate new information into existing structures or modify those structures based on new experiences (Bormanaki & Khoshhal, 2017). Vygotsky adds that learning systems and interfaces function as scaffolding, activating and strengthening schemata through guided interactions that gradually fade as learners progress within their Zone of Proximal Development (Margolis, 2020). Cognitive Load Theory further emphasizes that well-developed schemata reduce cognitive load by enabling more efficient automated processing of information (Sweller, 2020). Empirical evidence from Wirzberger et al. (2018) supports this view, showing that as schema acquisition increases, cognitive load decreases logarithmically.

Together, these theories clarify why schemata critically influence how learners process information, interact with online systems, and experience learning benefits.

Consequently, the success of an online learning system and the students' success in using it largely depend on their schemata (Liu & Cheng, 2025; Noreña et al., 2025) and are related to the system and learning process (Magsamen-Conrad & Dillon, 2020; Truong, 2016). Despite this, studies evaluating online learning systems using the DeLone and McLean model have rarely incorporated schemata as a contributing factor. For instance, many studies have largely overlooked the role of schemata (Sweller, 1988; Lutfi, 2023). Given the rapid advancement of online learning and its technological infrastructure, understanding how schemata influence system use and perceived benefits is increasingly important (Al-Maroof et al., 2022). These gaps highlight the need not only to evaluate system effectiveness through technical indicators, but also to examine how learners' cognitive structures shape their engagement with online learning systems.

At the same time, despite extensive use of the DeLone and McLean IS Success Model in online learning research, prior studies have primarily focused on technical and service-related determinants of system success, with limited attention to learner-level cognitive mechanisms that may condition how system qualities translate into perceived benefits. Moreover, while learning equity is frequently invoked in discussions of online education, empirical IS research rarely examines how system success interacts with learners' prior knowledge structures to support conditions associated with equitable learning. This study addresses this gap by integrating schemata into the IS Success Model to examine how cognitive frameworks shape the relationships between system qualities, user perceptions, and perceived system-related benefits that may support equitable online learning conditions.

This focus is particularly relevant in self-paced learning environments, where schemata serve as a critical cognitive component (Anderson et al., 1978; Jung et al., 2022). Schemata allow learners to make sense of new information by linking it to their existing knowledge base (Neumann & Kopcha, 2018). This cognitive process enables students to construct meaning by aligning new content with their prior experiences (Halkias, 2015). Online learning technologies can further enrich students' schemata through opportunities for interaction and reflection (Zheng & Warschauer, 2015). Therefore, this study seeks to examine and clarify the influence and position of schemata within the DeLone and McLean framework in order to better understand how successful information systems generate benefits that may support equitable online learning conditions.

Research Questions

1. Is the Information System Success Model a good fit for examining students' schemata in relation to system-related benefits that may support equitable online learning conditions?
2. What role do students' schemata play within the Information System Success Model in shaping equity-enabling system benefits?
3. How do students' schemata influence system-related benefits associated with online learning equity within the framework of the Information System Success Model?

Together, these questions examine model suitability (RQ1), the structural positioning of schemata (RQ2), and the mechanisms through which schemata shape perceived system-related benefits associated with equity (RQ3).

Literature Review

Information Systems Success Model

The Information Systems (IS) Success Model comprises six interrelated components: system quality, information quality, service quality, use/intention to use, user satisfaction, and net benefits (DeLone & McLean, 2003). According to the model's proponents, system quality refers to how effectively a technology system functions. In the context of online learning, this includes technical aspects of e-learning platforms such as speed, reliability, and the system's capacity to meet user needs (Dhawan, 2020; Sarrab et al., 2016). Recent research suggests that high system quality, which is characterized by platform reliability and a user-friendly interface, can positively affect both user satisfaction and intention to use the system (Tsai et al., 2014; Xiao et al., 2024).

Information quality is another key component, encompassing attributes such as accuracy, completeness, relevance, timeliness, and consistency. Users who receive information that is accurate, relevant, timely, and easy to understand are more likely to be satisfied and engage regularly with the system (Molinillo et al., 2021). In the online learning context, this refers to the quality of materials, exams, and feedback provided by the platform. High information quality, when aligned with user schemata, enhances satisfaction and intention to use the system. This ultimately leads to deeper engagement and improved learning outcomes.

Service quality refers to the extent to which support services delivered through the platform meet user expectations, whether from students, lecturers, instructors, or administrators (Ramírez-Hurtado et al., 2021). In online learning, this includes timely, responsive technical support and effective interactions within the system (Rughoobur-Seetah & Hosanoo, 2021). High service quality has been shown to increase student engagement, particularly when users feel supported in resolving technical or instructional issues (Baloran et al., 2021; Salas-Pilco et al., 2022). Students who are satisfied with their overall experience, whether in terms of support, system responsiveness, or content quality, tend to be more engaged and active participants in learning activities.

These three core dimensions, which are system quality, information quality, and service quality, jointly influence both intention to use and user satisfaction. According to DeLone and McLean (2003), intention to use is a strong predictor of actual system usage and, by extension, a key factor in determining system success (Alotaibi & Alshahrani, 2022; Lutfi, 2023). Meanwhile, user satisfaction reflects the degree to which users are content with their experience using the system. Research shows that user satisfaction mediates the relationship between system quality and perceived usefulness (Abdullah et al., 2025; Alkhawaja et al., 2022). Satisfied users are more likely to continue using the platform, increase their engagement, and derive greater educational benefits (Elmunsyah et al., 2023; Sabeh et al., 2021).

Ultimately, these factors contribute to the system's net benefits, which are the tangible outcomes users gain from using the system, such as improved understanding, mastery of content, and academic achievement (Sabeh et al., 2021; Wang et al., 2025). Net benefits are significantly shaped by user satisfaction (Çelik & Ayaz, 2022). A successful learning system enhances these benefits, leading to better collaboration, skill development, and overall learning outcomes (Ng et al., 2022). However, recent studies argue that schemata also play a critical role in enabling users to fully benefit from information systems (Wang & Yin, 2023), which suggests that cognitive frameworks must be considered alongside traditional success factors.

Online Learning Equity

Online learning equity refers to a systematic effort to reduce disparities in digital education by ensuring equal access, participation, learning experience, and outcomes for all students (Tate & Warschauer, 2022). One of the primary technologies used in online learning is the Learning Management System (LMS), which has been identified as a vital support system for both online and blended learning environments (Rahmi et al., 2022; Turnbull et al., 2021). Although LMSs hold great potential for promoting equity, various factors hinder their effective use and limit their ability to support all learners equally.

Students from rural or underserved communities often face barriers such as limited access to technology and internet connectivity (Gu, 2022; Nichuhovska et al., 2023). These access issues are compounded by individual differences in schemata, i.e., students' prior knowledge structures, that significantly influence how they process and apply new information (Gurlitt et al., 2012). As a result, these gaps can lead to unequal participation and outcomes in online learning, thereby exacerbating existing educational inequities (Çelik & Ayaz, 2022; Flynn, 2021).

While online learning is praised for its flexibility and accessibility, achieving equity requires more than just access. It requires thoughtful system design that considers diverse learner backgrounds and prior experiences (Goodman et al., 2018). In this context, information systems used in online learning will only function optimally if they accommodate learners' schemata throughout the instructional process. Therefore, this study explores the integration of schemata into the DeLone and McLean (2003) framework, aiming to examine system-related factors that may support online learning equity by understanding how cognitive structures influence engagement and system benefits.

It is important to clarify the scope of equity within the present study. Although online learning equity serves as a central theoretical lens, this study does not operationalize equity as a standalone construct in the empirical model. Instead, the analysis focuses on perceived system-related benefits, such as accessibility, flexibility, participation, and accommodation of learning styles, which prior research has identified as enabling conditions for equitable learning environments (Tate & Warschauer, 2022). Thus, equity is examined conceptually through the extent to which online learning systems provide conditions that may support fair learning opportunities, rather than through direct measurement of equity outcomes.

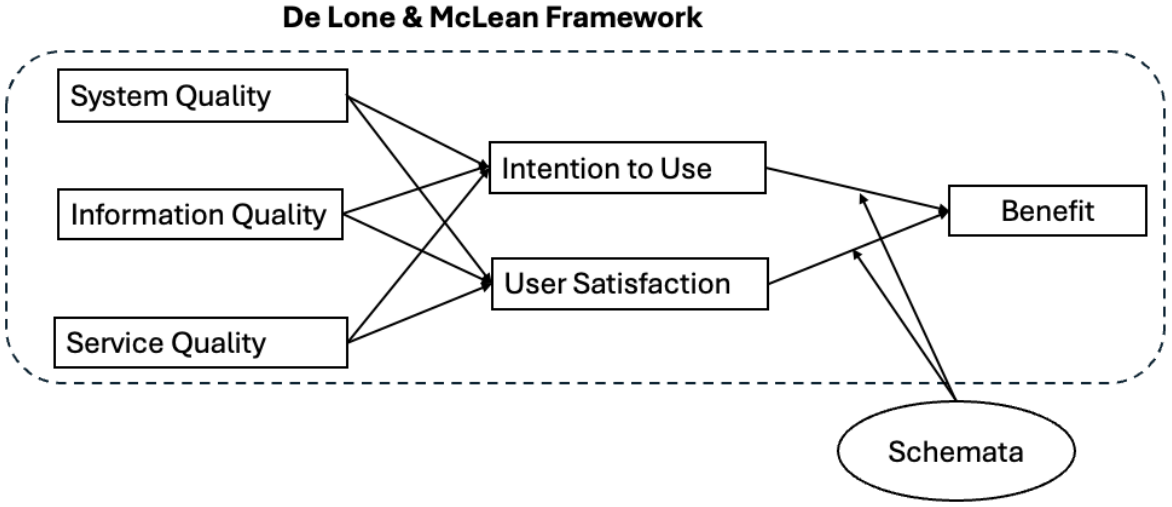
Schemata Theory

In the context of online learning, schemata refer to knowledge structures or cognitive frameworks developed through previous learning experiences. These structures enable individuals to interpret and organize new information (Jung et al., 2022) presented through digital platforms. The presence of schemata is essential in online learning settings (He, 2020), as students are required not only to grasp academic content but also to navigate digital interfaces, understand system processes, and manage their learning strategies independently (Jung et al., 2022; Koh, 2017). Schemata can further influence the relationship between satisfaction, intention to use, and the perceived benefits of online learning systems. Students who possess more developed cognitive frameworks related to online learning are often more capable of managing the learning process effectively. This remains true even when the quality of the systems and services available to them is consistent across users. Despite this, research over the past decade has not yet examined the position of schemata within the Information Systems Success Model (Sabeh et al., 2021). This study addresses that gap by identifying and explaining the position and function of schemata within the DeLone and McLean framework as they relate to perceived system benefits.

The findings of this study reinforce the growing evidence that differences in cognitive schemata have a meaningful impact on student behavior and learning outcomes (Gurlitt et al., 2012), particularly in digital environments (Vuopala et al., 2016). As a result, schemata should be recognized as a moderating variable within the DeLone and McLean model. Its inclusion can enhance the understanding of what contributes to the effectiveness of online learning systems.

Figure 1

The Theoretical Framework



Methods

Research Design

This study employed a quantitative research design using a survey method to describe and analyze the relationships among variables. The study also aimed to test a proposed relationship model grounded in the Information Systems Success Model (DeLone & McLean, 2003) by examining the role of a moderating variable in shaping the benefits derived from using information systems that are associated with equitable learning conditions.

Participants

The participants in this study were university students with experience using online learning systems for at least one year. These students were drawn from two state universities in Indonesia, which share comparable institutional structures and online learning infrastructures. Both institutions offer teacher education programs that prepare prospective teachers and employ similar instructional designs that integrate online learning and Learning Management Systems (LMS) as core components of course delivery. As a result, students at both universities have comparable exposure to LMS-based learning environments and digital instructional practices.

The instrument was administered to students via a Google Form. The link was distributed at the end of the semester, after the lecture session had concluded. A total of 280 students were invited to participate, and 252 responses were collected. Out of the total respondents, 79% were female, and 21% were male. In terms of experience, 58.2% had at least one year of online learning experience, 25.1% had two years, and 16.7% had three years. While this sampling approach ensures contextual consistency across institutions, the findings should be interpreted as situated within public teacher education universities using LMS-based instructional designs, rather than as representative of all higher education contexts.

Measurement

The instrument used in this study was based on the dimensions of the IS Success Model as proposed by DeLone and McLean (2003), which includes the following constructs: System Quality, Information Quality, Service Quality, Intention to Use, User Satisfaction, and Net Benefits. In addition to these, this study introduces schemata as a moderating variable influencing the relationship between user experience and perceived benefits.

The schemata construct was operationalized to reflect learners' prior knowledge and cognitive readiness in online learning contexts. While the measurement items were drawn from validated instruments used in prior IS and educational research (see Table 1), their conceptualization is theoretically aligned with established work on schema theory, prior knowledge activation, and cognitive engagement in digital learning environments (Bruning et al., 2004; Kalyuga et al., 2003; Azevedo, 2005).

A questionnaire was developed to measure each construct in the proposed model. The items were adapted from validated instruments used in previous studies and were categorized under their respective dimensions. The full list of variables, items, and references is provided below.

Table 1

Measurement Items by Variable and Reference

No.	Variable	Item	References
1.	System Quality	This system is easy to use. This system provides accurate information. This system is reliable and performs consistently. The interface of the system is user-friendly. The system response time is satisfactory.	DeLone & McLean (2003)
2.	Information Quality	The information provided by the system is relevant to my needs. Information is presented clearly and is easy to understand. This information is up-to-date and timely. This information is well-organized. This information meets my needs for decision-making.	DeLone & McLean (2003)
3.	Service Quality	Support services related to this system are easily accessible. Help and support from service staff meet my needs. Responses to my questions are provided quickly. Overall service quality meets my expectations. Service staff have extensive knowledge of this system.	DeLone & McLean (2003)
4.	Intention to Use	I frequently use this system for my tasks. I depend on this system to complete my work. This system is my preferred tool for information retrieval. I am confident that I use this system effectively.	DeLone & McLean (2003)
5.	User Satisfaction	I am satisfied with my overall experience using this system. I would recommend this system to others. I feel comfortable using this system regularly.	DeLone & McLean (2003)
6.	Schemata	My access to learning resources has increased with the use of the online learning platform.	Roh & Won (2023)

		I have prior knowledge that encourages me to actively engage with the online learning platform.	You (2022)
		Prior knowledge is supported by the online environment for equity.	Phillips et al. (2012)
		My information retention is enhanced by the availability of diverse learning resources.	Gorman & Rentsch (2017)
		Previous learning experiences help me complete tasks on the online learning platform.	DeFeo & Caparas (2014)
7.	Benefits	I benefit from the increased accessibility of the online learning system.	DeLone & McLean. (2003); Buttimer et al. (2022)
		I experience flexible learning opportunities with the system.	DeLone & McLean (2003); Reedy (2019)
		My learning style is accommodated by the variety of learning modalities available.	DeLone & McLean (2003)
		I actively participate in learning with this system.	DeLone & McLean (2003); Martin et al. (2020)
		Online learning is designed based on DeLone & McLean's principles.	DeLone & McLean (2003); Abdelkareem, (2021)

It is important to note that although learning equity informs the theoretical framing of this study, it is not measured directly as a separate construct. The 'Benefits' variable captures students' perceptions of system-related outcomes, such as increased accessibility, flexibility, participation, and accommodation of learning preferences, that are widely associated in the literature with equitable learning conditions. Therefore, equity is addressed indirectly through learners' perceived benefits rather than through explicit indicators of fairness or barrier reduction.

In addition, several sources of potential bias of this research should be also acknowledged. Self-reflection bias may have occurred because participation was voluntary, which may affect the representativeness of the sample. Institutional bias is also possible, as data were collected from only two public universities, which may limit the representativeness of the sample. To address these concerns, the questionnaire link was distributed to all students at each institution to maximize participation, and anonymity was maintained to encourage honest responses. Respondent characteristics such as academic major and year of study were also compared with available university population data to assess sample representativeness.

The instrument was validated through multiple steps to ensure accuracy and reliability. Consistent with PLS-SEM procedures, construct validity was primarily assessed through convergent and discriminant validity, while expert review, involving three specialists, was used to establish content validity. Construct validity was evaluated through indicator loadings, composite reliability, and AVE values. To measure internal consistency, reliability analysis was conducted using Cronbach's Alpha, with values of 0.70 or higher considered acceptable and indicative of reliable constructs (see Table 3 for full results of the reliability test).

Data Analysis

After the basic assumptions were verified and the research data were declared valid, the next step was to conduct a Structural Equation Modeling (SEM) analysis using SmartPLS statistical software. After the structural and measurement models were evaluated, the hypothesis was tested by examining the path coefficient and significance value (p-value). A hypothesis is considered supported when the p-value is less than or equal to 0.05 and the path coefficient is in the expected direction. If the path coefficient indicates the expected direction (positive or negative), the relationship between the variables is considered valid. Consistent with common practice in PLS-SEM research, hypotheses were evaluated using a significance level of $\alpha = 0.05$.

Results

Model Assumption Test

Convergent validity.

Convergent validity tests the ability of each indicator to explain the latent variable. According to (Hair Jr et al., 2017) and (Chin, 1998), a loading factor value greater than 0.50 is considered to indicate an acceptable level of convergent validity. Similarly, Ghozali (2016) states that an indicator is considered valid if its outer loading value exceeds 0.50. As shown in Table 2, all indicators across the seven constructs meet this requirement, with most values above 0.75, demonstrating strong relationships between the indicators and their corresponding constructs. Construct reliability was also confirmed through Composite Reliability (CR) values above 0.70 (Nunnally & Bernstein 3rd, 1994) and AVE value exceeding 0.50 (Chin, 1998), which indicates that the constructs exhibit both adequate reliability and convergent validity.

Table 2

Outer Loading Value of Each Variable

	Information Quality	Intention to Use	Schemata	Service Quality	System Quality	User Satisfaction	Benefit
KS2					0.757		
KS3					0.822		
KS4					0.777		
KS5					0.814		

KS6				0.717		
QI1	0.854					
QI2	0.812					
QI3	0.859					
QI4	0.812					
QI5	0.813					
QS1			0.833			
QS2			0.755			
QS3			0.840			
QS4			0.823			
QS5			0.811			
bene1						0.853
bene2						0.886
bene3						0.813
bene4						0.716
bene5						0.874
satis1					0.860	
satis2					0.926	
satis3					0.895	
satis4					0.883	
scm1			0.876			
scm2			0.864			
scm3			0.843			
scm4			0.845			
scm5			0.813			
use1		0.841				
use2		0.862				
use3		0.799				

Table 3 below shows that all constructs meet the recommended criteria for internal consistency, with Cronbach's alpha and composite reliability (CR) values exceeding 0.70. Furthermore, all AVE values are above 0.50, confirming that each construct explains more than half of the variance of its indicators. These results collectively indicate that the measurement model demonstrates strong reliability and convergent validity, and that the constructs are measured with high internal consistency.

Table 3

Composite Reliability Variable Value

Construct Model	Cronbach's alpha	Composite reliability (rho_a)	**Composite reliability (rho_c) CR**	AVE
Information Quality	0.887	0.888	**0.917**	0.690
Intention to Use	0.781	0.781	**0.873**	0.696

Schemata	0.896	0.899	**0.923**	0.707
Service Quality	0.871	0.875	**0.907**	0.661
System Quality	0.837	0.843	**0.885**	0.606
User Satisfaction	0.913	0.914	**0.939**	0.794
Benefit	0.886	0.897	**0.917**	0.690

Discriminant validity test.

Discriminant validity is conducted to ensure that each concept in each latent model is distinct from the other variables (Ghozali, 2016). It is assessed using two approaches: the Fornell–Larcker criterion and cross-loadings (Ringle et al., 2012; Salloum et al., 2019). According to the Fornell–Larcker criterion, discriminant validity is confirmed when the square root of a construct's AVE is greater than its correlations with other constructs (Fornell & Larcker, 1981a, 1981b; Mahande et al., 2024; Mehmetoglu & Venturini, 2021). Cross-loading analysis further requires that each indicator loads higher on its own construct than on others (Sekaran & Bougie, 2016; Hair Jr. et al., 2017). As presented in Table 4, all constructs meet the Fornell–Larcker criterion, with each construct's AVE root exceeding its correlations with other latent variables. This confirms that the constructs are empirically distinct and that the model meets the requirements for discriminant validity (Kock, 2023).

Table 4

Fornell Larcker (Correlation Between Factors and Root AVE)

Construct	Information Quality	Intention to Use	Schemata	Service Quality	System Quality	User Satisfaction	Benefit
Information Quality	0.830						
Intention to Use	0.629	0.834					
Schemata	0.685	0.664	0.841				
Service Quality	0.805	0.626	0.636	0.813			
System Quality	0.791	0.575	0.614	0.692	0.778		
User Satisfaction	0.681	0.757	0.699	0.673	0.699	0.891	
Benefit	0.665	0.790	0.749	0.688	0.650	0.795	0.831

Collinearity test.

The collinearity test, also known as the multicollinearity test, is used to determine whether there is inequality in variance and residuals within an observation in a regression model. If the VIF value is no more than 5, it is concluded that there is no collinearity between the statements. As shown in Table 5, all VIF values fall below the recommended upper limit of 5.00, indicating that multicollinearity is not present among the indicators or interaction terms. This

means that the predictors do not exhibit problematic levels of shared variance, and each variable contributes uniquely to explaining the dependent variables in the model.

Table 5

Variance Inflation Factor Variable Value

	VIF
KS2	1.706
KS3	1.916
KS4	1.728
KS5	1.875
KS6	1.480
QI1	2.434
QI2	2.011
QI3	2.582
QI4	2.077
QI5	1.929
QS1	2.159
QS2	1.765
QS3	2.138
QS4	2.431
QS5	2.380
bene1	2.870
bene2	3.334
bene3	2.046
bene4	1.743
bene5	2.699
satis1	2.471
satis2	3.853
satis3	3.175
satis4	2.842
scem 1	1.934
scem 2	3.014
scem 3	3.303
scem 4	2.503
scem 5	2.465
use1	1.706
use2	1.867
use3	1.464
Schemata x Intention to Use	1.000
Schemata x User Satisfaction	1.000

Reliability test.

Next, the instrument's validity and reliability are tested. Based on Composite Reliability values all exceeding 0.7, it is concluded that the instrument used is valid and reliable (see Table 3 for full results of the reliability test).

Structural Model Test and Model Fit

To determine the structural relationship between latent variables, hypothesis testing is conducted by analyzing the path coefficients between those variables. This involves comparing the p-value with an alpha level of 0.05 or evaluating the t-statistic, which must exceed 1.96 to be considered significant. Both the p-value and t-statistic are obtained from the SmartPLS output using the bootstrapping method. Hypothesis testing is done by comparing the t-statistics obtained from the bootstrapping results with the critical t-value of 1.96, as recommended by Hair Jr. et al. (2017). If the t-statistic value for each hypothesis exceeds this threshold, the hypothesis is considered accepted or supported. The details of the structural model test results can be seen in Table 6.

As shown in Table 6 and Figure 2, system quality and service quality have significant positive effects on both intention to use and user satisfaction, while information quality significantly affects intention to use but not user satisfaction. Intention to use and user satisfaction both significantly predict perceived benefits. In addition, schemata have a significant direct effect on benefits and significantly moderate the relationships between intention to use and benefits, as well as between user satisfaction and benefits.

Table 6

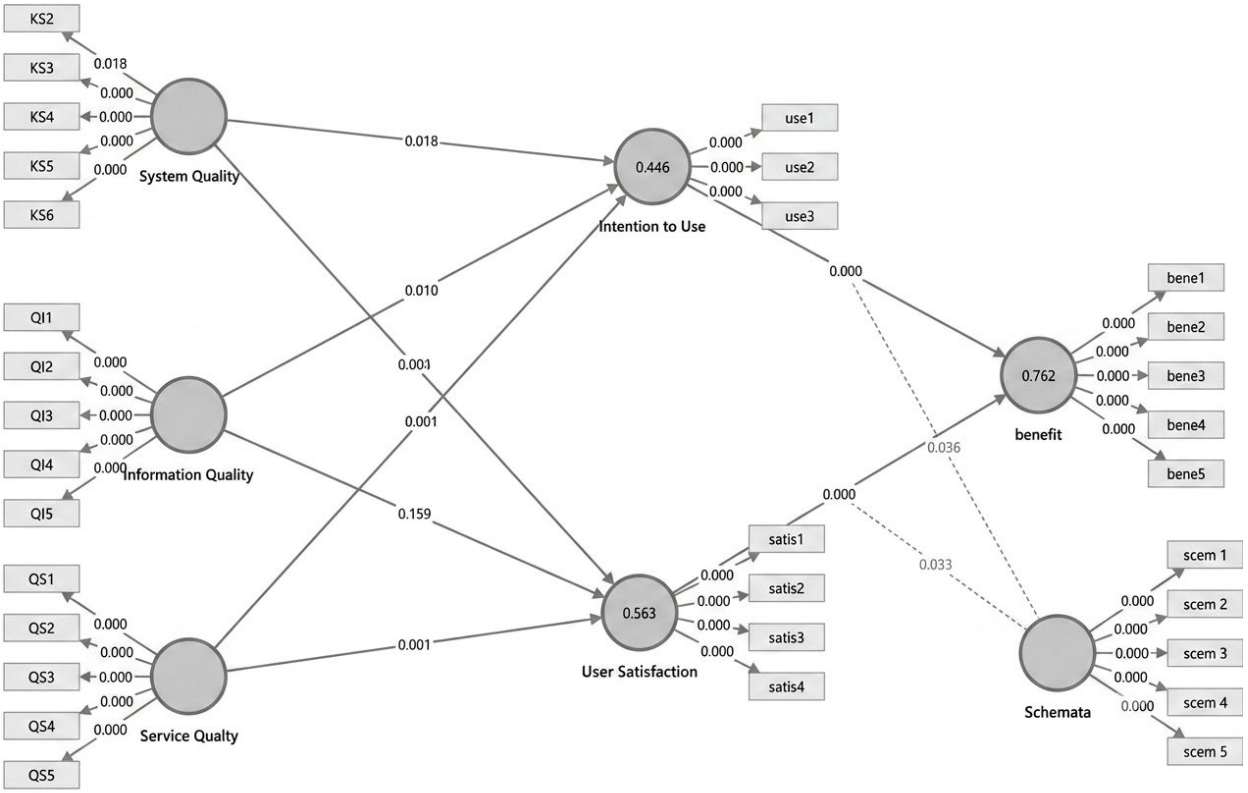
Results of the Path Model Analysis

Path Model	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Information Quality -> Intention to Use	0.248	0.241	0.096	2.572	0.010
Information Quality -> User Satisfaction	0.140	0.135	0.100	1.408	0.159
Intention to Use -> benefit	0.403	0.405	0.067	6.008	0.000
Service Quality -> Intention to Use	0.315	0.318	0.092	3.436	0.001
Service Quality -> User Satisfaction	0.293	0.300	0.085	3.459	0.001
Schemata M -> benefit	0.280	0.280	0.058	4.831	0.000
System Quality -> Intention to Use	0.161	0.169	0.068	2.376	0.018
System Quality -> User Satisfaction	0.385	0.386	0.078	4.921	0.000
User Satisfaction -> benefit	0.285	0.284	0.070	4.054	0.000
Schemata M x User Satisfaction -> benefit	-0.134	-0.130	0.063	2.130	0.033

Schemata M x Intention to Use -> Benefit	0.122	0.118	0.058		2.098	0.036

Figure 2

SEM Analysis



Following hypothesis testing, overall model fit was assessed to evaluate how well the proposed structural model represents the observed data. The standardized root mean square residual (SRMR) value was 0.078. Consistent with recommendations for PLS-SEM (Hair et al., 2021), an SRMR value below 0.08 indicates acceptable model fit, suggesting that the proposed model adequately represents the data.

Discussion

Before interpreting these findings, it is important to clarify the role of learning equity in this study. While equity is a guiding theoretical concern, it is not measured directly in the structural model. Instead, the findings are interpreted in terms of perceived system-related benefits that the literature associates with more equitable learning conditions, such as improved access, flexibility, participation, and learner accommodation. The discussion therefore focuses on how schemata influence learners' ability to translate system use and satisfaction into these equity-enabling benefits.

This study explores the role of schemata within the Information Systems (IS) Success Model, particularly in supporting equity-related learning conditions in online learning. The findings indicate that schemata function effectively as a moderator variable within the model. Taken together, the findings suggest that experiential and support-related system qualities play a more decisive role in shaping perceived benefits than information quality alone. This pattern indicates that how learners experience and interact with the system may matter more than content attributes in translating system use into meaningful benefits. This result aligns with Urbach and Ahlemann (2010), who found that user experience has a stronger influence on user satisfaction than the quality of information itself. Together, these initial findings highlight the importance of examining not only technical system attributes but also the cognitive factors that shape how learners interpret and respond to online learning environments.

Moreover, the study reveals that both intention to use and user satisfaction positively and significantly affect net benefits associated with conditions that may support equitable online learning. In particular, the relationship between user satisfaction and net benefits underscores user satisfaction as a critical link connecting system quality with the actual benefits perceived by users (Sachan et al., 2018). This reinforces the importance of ensuring high user satisfaction to maximize the impact of system improvements.

The findings indicate that schemata have a significant direct effect on perceived benefits and function as a moderating factor in the relationships between user satisfaction, intention to use, and benefits. This moderation suggests that learners' cognitive frameworks condition how effectively positive system perceptions are translated into meaningful outcomes. Students with more developed schemata are better able to interpret their satisfaction with the system and their intention to use it, resulting in higher perceived benefits, whereas learners with weaker schemata may struggle to convert similar system experiences into comparable gains.

These patterns are consistent with established cognitive learning theories. From a constructivist perspective, Piaget conceptualized schemata as evolving cognitive structures through which learners assimilate and accommodate new information (Piaget, 1970). Building on this view, Vygotsky's theory of the Zone of Proximal Development (ZPD) emphasizes that learning occurs most effectively when learners receive scaffolding that supports the gradual internalization of knowledge and strengthens schema development until independent performance is achieved (Vygotsky, 1978).

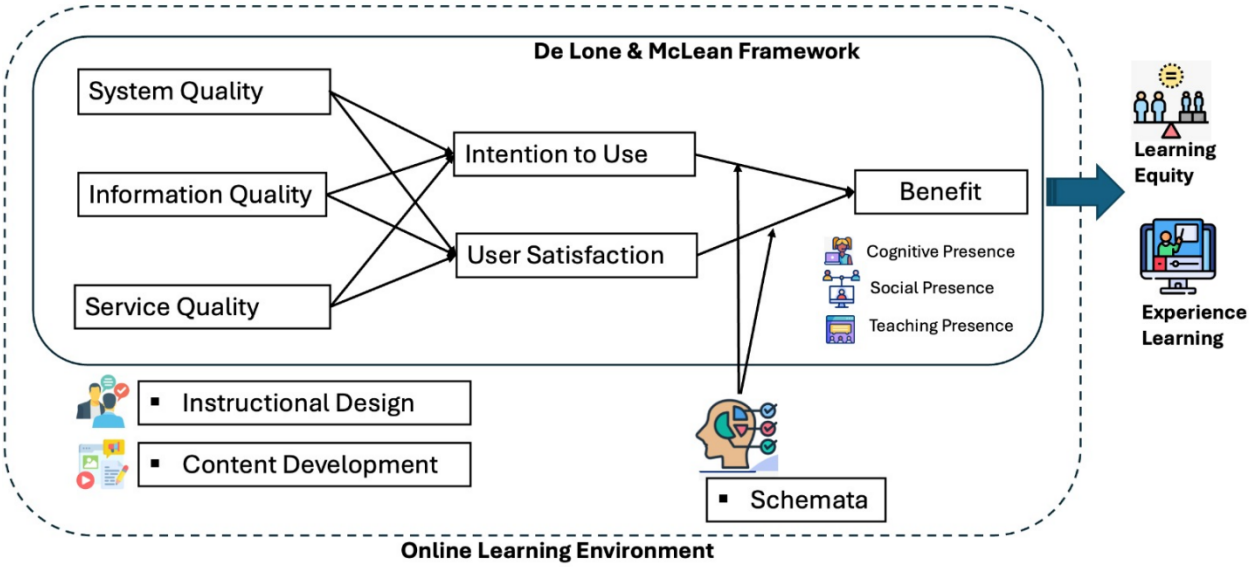
Complementing these perspectives, Cognitive Load Theory explains how well-developed schemata reduce extraneous cognitive load by enabling more efficient processing of complex information (Sweller, 1988; Sweller et al., 2023). Contemporary research further demonstrates that instructional designs that activate prior knowledge and provide structured scaffolding facilitate schema construction and improve learners' capacity to process information independently in digital environments (Sweller, Ayres, & Kalyuga, 2023). Together, these theories clarify how schemata, scaffolding, and cognitive load operate as distinct yet interrelated mechanisms shaping learners' engagement and outcomes in online learning systems.

The conceptual model highlights schemata as a key cognitive mechanism through which system quality dimensions and user perceptions are translated into perceived benefits. Rather than operating independently, system quality, user satisfaction, and intention to use interact with learners' existing cognitive frameworks, shaping how effectively system features are interpreted and used.

This model emphasizes that schemata function not only as cognitive filters but also as facilitators of meaning-making in online learning environments. When system design and instructional features align with learners' prior knowledge, students are better positioned to engage with content, navigate the system efficiently, and derive meaningful benefits. In this way, schemata help explain why similar system conditions may result in different learning experiences across learners and how system-level factors can support conditions associated with learning equity.

Figure 3

Conceptual Representation of the Interaction Between Schemata, System Quality Dimensions, User Perceptions, Perceived Benefits, and Equity-Related Learning Conditions Within the Online Learning Environment



Building on this framework, schemata also play a crucial role in shaping learners' cognitive engagement and their ability to derive meaningful benefits from online learning systems. By guiding how learners interpret and process online content, schemata influence how effectively learners make sense of instructional materials and sustain meaningful engagement (Shi et al., 2025; Bong et al., 2023). Given this role, online learning platforms and pedagogical approaches should be intentionally designed with schema theory in mind. Understanding how learners' prior knowledge shapes cognitive processing allows lecturers and instructional designers to create learning experiences that are more effective, relevant, and responsive to learner needs (D'Souza et al., 2023). For instance, enhancing system quality in ways that align

with users' prior knowledge can increase satisfaction and, in turn, amplify the benefits students derive from the system.

Leveraging schema theory also enables designers to create content, tasks, and activities that connect with learners' existing cognitive structures, thereby strengthening both cognitive and social presence through interaction and shared meaning-making (D'Souza et al., 2023). Such schema-aware design may contribute to conditions conducive to more equitable learning experiences, as students with varied backgrounds are better able to access, interpret, and benefit from online learning. Thus, supporting equity in online learning requires attention not only to system quality but also to learner-related factors, such as self-efficacy, motivation, and interface usability, that interact with cognitive structures like schemata to shape engagement and comprehension (Shi et al., 2025; Lin et al., 2022).

In this context, the significant moderating effect of schemata on the relationship between intention to use and perceived benefits provides further practical insight. Consistent with findings by Alraimi, Zo, and Ciganek (2015) in MOOC environments, learners with stronger schemata are better able to translate their intention to use online systems into meaningful benefits. As a result, learners with weaker schemata may require additional support features, i.e., such as scaffolding, guided navigation, or introductory resources, to bridge this gap and fully benefit from system use.

While theoretical insights deepen the interpretations of the findings, certain methodological limitations should be acknowledged. The sample was drawn from two public universities in Indonesia, and this institutional context may have shaped students' experiences with online learning systems. Factors such as governance structure, resource allocation, digital infrastructure, and student demographics in public universities may influence how system quality, support services, and learning benefits are perceived. As a result, the findings should be interpreted as contextually situated rather than universally generalizable, particularly when considering private institutions or international higher education settings. Future research could broaden the sample by incorporating students from additional institutions, including those in other countries. Moreover, this study focused exclusively on online learning modes. Subsequent studies could extend the scope to compare different course formats such as MOOCs, blended learning, and traditional in-person classes, and incorporate a wider range of academic disciplines across both the sciences and social sciences to enhance the robustness of the findings.

The implications of this study highlight opportunities for leveraging adaptive learning design to improve learning equity and effectiveness. Adaptive learning systems can use the insight gained here to dynamically adjust content difficulty based on students' schemata and cognitive load. Artificial Intelligence (AI), with its capacity for personalized learning pathways, can enhance schema formation and system usability by predicting student needs and tailoring instruction accordingly. Lecturers also play a critical role by providing appropriate scaffolding to support the adaptation process without overloading cognitive resources. In online learning contexts, learning analytics dashboards within Learning Management Systems (LMS) can visualize student progress, track schema development, and detect moments requiring intervention, enabling lecturers to offer timely and data-driven support. The integration of these technologies enhances learning efficiency by aligning instructional pathways with individual

cognitive states and performance patterns to promote more meaningful and sustainable learning outcomes. These implications reinforce the broader argument that addressing cognitive diversity, through adaptive systems and structured support, is essential for advancing equity in online learning environments.

Conclusions and Recommendations

The Information System Success Model (DeLone & McLean, 2003) provides a comprehensive framework for understanding how system quality, information quality, and service quality influence both user satisfaction and perceived benefits in online learning environments. This study extends that framework by demonstrating that schemata function as a significant moderating factor, particularly in the relationships between user satisfaction and perceived benefit, as well as intention to use and perceived benefit. The findings show that learners with limited prior knowledge or weaker schemata may not derive meaningful benefits solely from intending to use the system; instead, they require scaffolding, personalized support, or introductory materials to bridge cognitive gaps. As such, users with stronger schemata are more likely to translate their system satisfaction and intention to use into actual learning benefits, especially when the platform assumes a certain level of prior understanding. These findings highlight that learners' cognitive structures play a pivotal role in mediating how system attributes translate into educational value, and further reinforce the importance of schema-aware design principles emphasized in the discussion.

Given this moderating role, online learning systems need to be designed with features that accommodate variations in schemata. Adaptive functionalities and user-friendly interfaces can help bridge cognitive differences among users and support conditions conducive to more equitable learning outcomes. Furthermore, schemata are essential in explaining individual differences in how users perceive and experience the benefits of online learning. Therefore, integrating psychological and cognitive factors such as schemata into the IS Success Model provides a more nuanced and holistic understanding of how learners engage with technology in higher education contexts. Based on the study's findings, it is recommended that future system designs address not only the technical aspects, such as system, information, and service quality, but also consider user-related factors such as self-efficacy, learning motivation, interface usability, interface design, user interface, and prior experience. Taking these elements into account will enhance the effectiveness of online learning systems and support broader learning equity goals. In the end, embedding cognitive considerations into online learning design represents a critical step toward supporting conditions that increase the likelihood that learners, regardless of prior knowledge, can achieve meaningful and equitable learning experiences.

Declarations

Conflicts of Interest Statement

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

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Exploring the Relationship Between Teaching Presence, Self-Regulation, and Co-Regulation in Online Courses

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Abstract
This study explores the relationship between teaching presence and students' self- and co-regulation, in online learning courses. Data were collected from 283 students enrolled in online courses using the Teaching Presence Scale of the Community of Inquiry survey and a Shared Metacognition Questionnaire. Descriptive analyses revealed that students perceived their instructor's course design practices, particularly clear communication of goals, deadlines, and instructions, as the most influential component of teaching presence in enhancing their learning experiences. Students reported strong self-regulation, especially in maintaining awareness of effort and motivation. For co-regulation, while students recognized the importance of considering and listening to peer feedback, the greater variability in these ratings suggested differing levels of value placed on these collaborative practices. Regression analyses showed that both course design and facilitation significantly predicted self-regulation, explaining 25.9% of its variance, whereas facilitation alone predicted co-regulation, accounting for 26% of its variance. These findings emphasize the importance of intentional course design and active facilitation in fostering self-regulation and co-regulation in online courses. The study contributes to advancing the Community of Inquiry framework by integrating metacognitive constructs and offers actionable strategies for designing online courses that promote autonomy and shared responsibility for learning.

Keywords: Online courses, teaching presence, self-regulation, co-regulation, regulated learning

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As online education continues to expand, educators and researchers are increasingly focused on designing learning environments that cultivate students' sense of presence and enhance their ability to regulate learning effectively (Liao et al., 2023; Maré & Mutezo, 2025). Yet, instructors struggle with issues of quality due to the "requirement of higher-level self-directed learning skills and greater difficulties in enabling effective human interactions" (Xu & Xu, 2019, p. 26). To enhance the quality of online learning for students, it is important to use strategies that can support the development of students' regulatory processes in shared learning environments (Garrison, 2022). The Community of Inquiry (CoI) framework offers a foundation for developing such environments, emphasizing the interplay of cognitive presence, teaching presence, and social presence to support meaningful learning experiences (Garrison et al., 2010).

Among the CoI elements, teaching presence plays a vital role in shaping learner engagement and fostering regulated learning (Akyol, 2013; Garrison et al., 2000). Defined as "the design, facilitation, and direction of cognitive and social processes to realize personally meaningful and educationally worthwhile learning outcomes" (Anderson et al., 2001, p. 5), teaching presence has been linked to the development of both self-regulation (SR) and co-regulation (CoR). SR refers to learners' ability to plan, monitor, and evaluate their cognitive and motivational processes (Hadwin et al., 2017) while CoR involves collaborative efforts to manage learning through shared strategies and peer support (Järvelä et al., 2018).

In online learning contexts, where face-to-face is often absent, students must rely on self-regulatory skills such as goal setting, time management, and self-monitoring to navigate their learning independently (Doo et al., 2023). Simultaneously, CoR becomes essential for sustaining motivation and deepening understanding through peer interaction and shared metacognitive practices (Garrison & Akyol, 2015). Teaching presence fosters both SR and CoR, which together drive better engagement, satisfaction, and achievement (Doo et al., 2023; Garrison, 2022). Illuminating which aspects of teaching presence most effectively strengthen students' SR and CoR can guide practitioners to prioritize design features and facilitation strategies that enhance learner autonomy, collaboration, and ultimately course success (Broadbent & Fuller-Tyszkiewicz, 2018; Shea & Bidjerano, 2024).

While the importance of a strong teaching presence is recognized, limited research has examined its relationship with student-driven behaviors like SR and CoR of learning (Maré & Mutezo, 2025). There is a growing need to explore how teaching presence influences students' awareness and use of regulatory strategies, and how these perceptions relate to learning outcomes in online environments (Garrison, 2022; Sadaf et al., 2022). Specifically, understanding the relationship between teaching presence and regulation can inform course design and instructional practices that better support regulated learning in online environments (Garrison & Akyol, 2015; Maré & Mutezo, 2025).

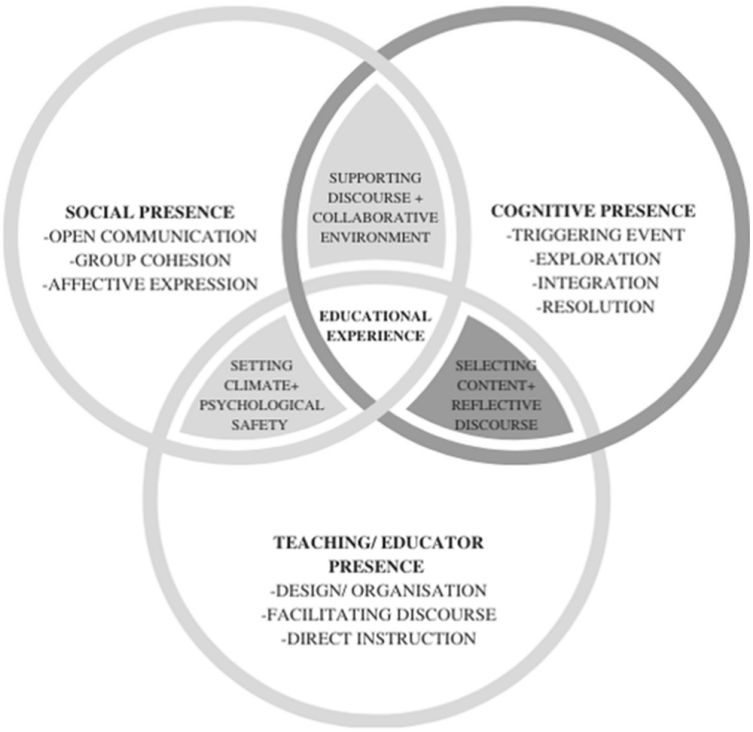
Theoretical Framework

This study is grounded in the Community of Inquiry (CoI) framework (see Figure 1) developed by Garrison, Anderson, and Archer (2001), which provides a robust model for designing and evaluating online learning environments through a social-constructivist lens (Castellanos-Reyes, 2020; Garrison, 2017; Swan, Garrison, & Richardson, 2008). The CoI

framework posits that meaningful learning occurs at the intersection of three core elements: cognitive presence, social presence, and teaching presence (Garrison et al., 2000). Social presence is about participants' social interaction in online learning environments, and cognitive presence guides the construction of meaning through reflection and discourse (Garrison et al., 2001). Teaching presence focuses on the design, facilitation, and direction of social and cognitive presence to achieve desired learning outcomes (Anderson et al., 2001).

Figure 1

Community of Inquiry Framework (Garrison et al., 2001)



Recent developments in the CoI framework highlight the role of metacognition, particularly SR and CoR, as residing between teaching and cognitive presence (Garrison, 2022). This intersection reflects the synergy between internal knowledge construction and collaborative learning activities. For example, cognitive presence supports the development of metacognitive skills through inquiry and reflection, while social presence creates a motivational climate that encourages regulatory behaviors. Teaching presence, in turn, fosters regulation by guiding learners to take personal responsibility for their learning and by facilitating collaborative knowledge building (Garrison, 2022). Each component of teaching presence contributes uniquely to regulatory development:

- Design and organization provide a structured environment for critical reflection and discourse, serving as a metacognitive map of the learning process.

- Facilitation supports the implementation of metacognitive strategies during learning activities.

- Direct instruction enhances collaborative learning by promoting awareness and management of learning processes, which can lead to improved academic performance (Garrison, 2022).

Garrison et al. (2010) emphasize that teaching presence is essential for establishing and sustaining the cognitive and social processes that underpin metacognition. Vuopala et al. (2019) found that prompting regulation activities—such as task-related monitoring—can help students engage in regulatory processes that support high-level knowledge co-construction. The CoI framework was selected for this study because it emphasizes both the personal (reflective) and shared (collaborative) dimensions of the learning experience (Garrison et al., 2001). It offers a comprehensive lens through which to examine the relationship between teaching presence and students' regulation in online learning environments (Garrison, 2022).

Literature Review

With the rapid expansion of online education, understanding the pedagogical strategies that foster meaningful learning experiences has become a priority for educators and researchers alike. Among the most well-established theoretical frameworks guiding this understanding is the Community of Inquiry (CoI) framework, which posits that the development of deep and meaningful online learning experiences relies on the interaction of three core elements: cognitive presence, social presence, and teaching presence (Garrison et al., 2000). Teaching presence, in particular, has garnered significant attention for its critical role in shaping students' learning outcomes by structuring the learning environment, supporting engagement, and guiding the learning process (Lowenthal & Dunlap, 2020).

Teaching Presence in Online Learning

Teaching presence, as defined within the Community of Inquiry (CoI) framework, encompasses three core components: instructional design and organization, facilitating discourse, and direct instruction (Anderson et al., 2001). Together, these elements contribute to a structured and supportive learning environment that fosters both cognitive engagement and social interaction. A robust teaching presence has been consistently linked to higher levels of student satisfaction, engagement, and perceived learning outcomes (Martin et al., 2018).

Recent research has underscored the critical role of instructional design in establishing clear expectations and guiding learners through the educational process (Anderson et al., 2001). Johnson et al. (2017) noted that the structure and organization of online courses play a critical role in promoting meaningful learning by fostering student motivation and encouraging task completion. Poorly designed courses can result in cognitive overload and disengagement, whereas well-structured courses promote learner autonomy, focus, and self-monitoring (Jaggars & Xu, 2016). For example, Chen and Chen (2025) found that teaching presence—which integrates explicit instruction with structured guidance—significantly enhances student engagement and cognitive presence. Similarly, Sadaf et al. (2023) found that students rated

course design elements, such as clearly communicated goals and timelines, more favorably than facilitation or direct instruction.

Facilitation, the second component of teaching presence, involves encouraging student participation, maintaining engagement, and fostering a collaborative learning environment (Anderson et al., 2001). Effective facilitation includes prompting discussion, validating student contributions, and modeling critical thinking—practices that strengthen both social and cognitive presence (Stenbom, 2018). In the context of regulated learning, facilitation plays a vital role in supporting the co-construction of knowledge by guiding learners to reflect on their thinking and respond to peer feedback (Garrison, 2022). Sadaf et al. (2023) further highlighted that facilitation significantly predicts both SR and CoR, suggesting that instructors who actively engage in facilitating discourse can meaningfully influence students' metacognitive development.

The third element, direct instruction, involves delivering content expertise, clarifying misconceptions, and synthesizing key concepts (Anderson et al., 2001). While its primary function is to ensure content accuracy and coherence, direct instruction also contributes to metacognitive development by modeling critical thinking and problem-solving strategies (Akyol & Garrison, 2011; Garrison & Akyol, 2015). However, its influence on metacognitive engagement may be less pronounced compared to instructional design and facilitation. Nonetheless, when integrated effectively, direct instruction can support learners in developing the cognitive tools necessary for reflective and strategic learning (Garrison & Akyol, 2015).

While strong teaching presence is associated with enhanced perceived learning and improved educational experiences, limited research exists on how students perceive the effectiveness of different strategies used to establish teaching presence in online learning environments (Watson et al., 2023). Vaughan and Wah (2020) concluded that teaching presence should "intentionally design, facilitate, and direct a collaborative constructive learning environment in order for students to learn how to co-regulate their learning" (p.1). This suggests to a need for research on exploring students' perceptions of the effectiveness of various instructional strategies for establishing teaching presence in online environments that support collaborative and co-regulated learning.

Self-Regulation and Co-Regulation in Online Learning

Scholarly research consistently demonstrates a strong relationship between regulated learning and online learning performance (Tsai et al., 2018; Zhao & Ye, 2020). While SR focuses on individual goal-setting and strategy use, CoR refers to the mutual regulation of learning processes among peers, typically within collaborative learning environments (Järvenoja et al., 2025). Together, these processes form the foundation of CoR learning, which is especially critical in online learning contexts where students often work independently or in small groups to navigate complex tasks. Kizilcec et al. (2017) emphasized that regulatory strategies—such as planning, monitoring, and evaluating one's learning—enhance goal-setting and improve learning outcomes.

Self-regulated learning (SRL) refers to a dynamic process in which learners actively and intentionally engage in setting learning objectives, while simultaneously monitoring and regulating their motivation, cognitive strategies, and behaviors in alignment with both their goals

and the contextual demands of the learning environment (Pintrich, 2000). Students with strong SRL skills are more likely to persist through challenges, remain engaged, and employ effective learning strategies (Broadbent & Poon, 2015). Snyder and Dringus (2014) found that effective instruction, motivation, and guidance are essential for fostering regulation and the co-construction of knowledge in online courses. Similarly, Morrison and Jacobsen (2023) concluded that enhanced teaching presence through timely, strengths-based and personalized feedback had the effect of supporting students' self-regulation—the development of learner agency—and therefore enhancing students' engagement and learning in an online course. Garrison (2022) highlighted that intentional planning for collaborative learning, the establishment of a learning community, and the promotion of reflection and discourse can significantly enhance metacognitive development. While these studies offer valuable insights into the determinants of regulation, there remains a gap in understanding how to effectively teach students to become more aware of and capable in regulating their learning processes in online environments.

CoR extends the concept of SR to collaborative contexts, where learners engage in CoR by monitoring and supporting each other's learning (Järvelä et al., 2018). Hadwin et al. (2017) describe CoR as a social process that involves motivation, setting goals, and assessing progress, all of which take place within the context of interactions with others and the support available in the surrounding social environment. This includes behaviors such as giving and receiving feedback, reflecting on group progress, and adapting strategies based on peer input. Chen and Chen (2025) demonstrated that CoR, when supported by distributed teaching presence, leads to higher levels of cognitive engagement and improved learning outcomes. According to Garrison (2017), the development of SR and CoR is influenced by several factors, including the quality of instructional design, the availability of structured collaboration opportunities, and the instructor's role in facilitating meaningful discourse. Garrison (2022) further emphasized the importance of instructional strategies that intentionally promote regulation and collaborative learning in online settings. These strategies include guided reflection, peer assessment, and structured discussion prompts that encourage students to articulate their thinking and respond to others. Such approaches not only support individual learning but also cultivate a shared responsibility for learning within the group, ultimately enhancing the overall effectiveness of online education (Garrison, 2017).

Reflection and discourse with SR and CR can inform students how they can improve their approach to learning (Garrison, 2022). Studies have examined metacognitive processes in collaborative learning contexts recognizing the importance of individual and social regulatory processes within a community of inquiry (Kilis & Yildirim, 2018; Koehler et al., 2020). A collaborative learning environment requires more engaged approaches to help learners construct new meaning and share understanding with others (Garrison & Akyol, 2015). Therefore, Garrison (2022) emphasized the importance of exploring shared learning environments and strategies that can support the development of students' regulatory processes.

Relationship Between Teaching Presence, Self-Regulation, and Co-Regulation

Strong teaching presence can significantly enhance metacognitive engagement by fostering a supportive learning environment that promotes reflection, dialogue, and SR. Facilitation strategies—such as the use of guiding questions, peer feedback, and the encouragement of perspective-taking—have been shown to support CoR by promoting

interaction and responsiveness among learners (Stenbom, 2018; Sadaf et al., 2023). Kizilcec et al. (2017) found that instructional interventions aimed at enhancing regulated monitoring—such as goal-setting prompts and reflective checkpoints—can lead to increased learner engagement and improved performance in online courses. Similarly, Wang and Liu (2019) found that "the design and organization, as well as facilitating discourse, can facilitate students' interaction, reduce the number of peripheral students, and facilitate students' collaborative knowledge construction, especially in the knowledge sharing, discovery, discussion, and application" (p. 370). These findings underscore the importance of instructional strategies that go beyond content delivery to actively support students in managing their own learning processes. When students perceive a high level of teaching presence, they are more likely to engage in reflective practices and collaborate effectively with peers (Garrison, 2011; Garrison & Akyol, 2015). This highlights the need for instructors to be intentional in their *course design* and *facilitation*, ensuring that learners are equipped with the necessary tools and guidance to regulate their learning effectively.

Although prior research has demonstrated a strong association between students' perceived teaching presence and learning outcomes in online courses (Caskurlu et al., 2020), there remains a notable gap in the literature regarding the relationship between the three presences—teaching, social, and cognitive—and regulated learning in online environments. For instance, Sadaf et al. (2022) investigated students' perceptions of SR and CoR in relation to online presence within a case-based course. Their findings indicated that teaching presence did not exhibit a statistically significant relationship with regulation, suggesting that students who perceived higher teaching presence were not necessarily more likely to demonstrate higher levels of regulation. In a subsequent study, Sadaf et al. (2023) further examined the relationship between teaching presence and SR and CoR in online case-based instruction. They found that among the components of teaching presence, only *direct instruction* significantly predicted students' perceived regulation. While these findings offer valuable insights into the role of teaching presence in regulated learning, both studies were limited to case-based instructional strategies. Sadaf et al. (2023) emphasized the need for future research to explore specific elements of teaching presence across diverse instructional contexts and disciplines. Such investigations could provide a more comprehensive understanding of how the three presences interact with students' regulation strategies in online learning, thereby strengthening and extending the findings of previous studies.

Purpose of the Study

Recent research highlights the importance of shared metacognition in enhancing learning experiences and outcomes in online environments, demonstrating that it supports critical reflection, planning, and CoR among learners within a group (Garrison, 2022; Garrison & Akyol, 2015; Sadaf et al., 2023). However, researchers suggest a need for more research to help further our understanding of how best to develop the awareness and regulatory strategies to monitor and manage learning processes that enhance student learning outcomes (Garrison, 2022; Sadaf et al., 2022). Therefore, the purpose of this study is to explore the students' perceptions of the role of teaching presence in determining their SR and CoR in online courses. The following questions guided this study:

1. How do students perceive teaching presence (*course design*, *facilitation*, *direct instruction)* in online courses?

2. How do students perceive their SR and CoR in online courses?

3. What is the relationship between students' perceived teaching presence, SR, and CoR in online courses?

Methods

Research Design

Prior research has emphasized the importance of teaching presence in online learning but has offered limited empirical evidence on how specific components interact to influence student metacognitive processes. To address this gap, validated instruments measuring teaching presence developed by Arbaugh et al. (2008) and shared metacognition developed by Garrison and Akyol, (2015) were selected to capture these underexplored dimensions. Regression analyses were used to examine predictive relationships among course design, facilitation, direct instruction, and students' self- and co-regulatory behaviors, thereby extending prior studies that primarily employed correlational or descriptive approaches.

Participants

For this study, convenient sampling was employed to collect data from students enrolled in an online course in a public university in the Southeastern United States. Students were invited to complete both the CoI survey and the Shared Metacognition Questionnaire. After data cleaning, a final sample of 283 students, most of whom provided demographic information. The majority of participants identified as female (72.9%, n = 183) followed by male (25.1%, n = 63), other (1.2%, n = 3), and preferred not to disclose (0.8%, n = 2). Nearly half of the participants (49.5%, n = 137) were between 21 to 25 years old. Most respondents (64.2%, n = 180) had taken more than four online courses, and a large portion (67.5%, n = 187) reported feeling very comfortable with participating in online courses. Table 1 provides detailed demographic information about the study participants.

Table 1

Demographic Information of Participants (n=283)

	N	%		N	%
Gender			Age		
Male	63	25.1	21–25	137	49.5
Female	183	72.9	26–30	39	14.1
Other & prefer not to say	5	2.0	31–35	37	13.4
Student status			36–40	19	6.8
Graduate certificate	25	9.2	More than 40	45	16.2
Master's	248	90.8	Comfort level with online discussions		
Number of online courses taken			Not at all	3	1.1
1	29	10.7	A little	28	10.1
2	39	14.2	Fairly	59	21.3
3	29	10.7	Very	187	67.5
4 or more	180	64.2			

Data Collection

Data were collected through an online survey administered during Spring 2023 using the online survey platform, Qualtrics. Recruitment was conducted through multiple channels to reach a diverse sample of online learners. Email invitations were distributed via professional organizations' list serves, social media platforms, and directly to the professors who teach online courses, requesting that they share the survey link to their students. Additionally, an announcement request was submitted through the university's Institutional Research Study Announcement platform to broaden participation.

Students were asked to reflect on one online course that they were currently taking or had taken most recently while completing the survey. This approach was intended to capture students' perceptions based on their most recent and relevant learning experiences, ensuring that their reflections were accurate and timely. The survey also collected demographic information, including academic program, gender, age, prior experience with online courses, and the level of the degree program.

Students were then asked to respond to two sets of survey questions—Students' teaching presence was measured using the CoI survey developed by Arbaugh et al. (2008), and the Shared Metacognition Questionnaire developed by Garrison and Akyol (2015) was used to measure shared metacognition (SR/CoR). Each item employs a 5-point Likert-type scale, from 1 = Strongly Disagree to 5 = Strongly Agree. Ratings on SR and CoR were represented by 13 items each. For teaching presence, "Design and Organization" was measured with 4 items, "Facilitating Discourse" was measured with 5 items, and "Direct Instruction" was assessed using 4 items. Both surveys have been previously validated, and validation results confirmed their robust reliability and validity (Arbaugh et al., 2008; Garrison et al., 2004; Shea & Bidjerano, 2009; Swan et al., 2008).

The Community of Inquiry (CoI) survey, including teaching presence, is a well-established and psychometrically robust instrument, supported by multiple validation studies across languages and contexts (Arbaugh et al., 2008; Kozan & Richardson, 2014; Yu & Richardson, 2015). More specifically, for instance, Stenbom (2018) conducted a systematic review across 103 empirical studies from 2008 to 2017, and reported that the CoI survey consistently produced valid and reliable results across varied online and blended learning contexts. The Shared Metacognition Questionnaire also demonstrates sound psychometric properties, with clear exploratory and confirmatory factor analysis evidence supporting its structure and use in collaborative learning research (Garrison & Akyol, 2015; Kilis & Yildirim, 2018). In addition, to further confirm the reliability of the included questionnaires, we utilized the current sample to obtain Cronbach's alpha values (Cronbach, 1951). For the SR subscale, α = .93; for the CoR subscale, α = .90. In terms of the three teaching presence subscales, the α values were .89, .92, and .77, respectively for course design, facilitation, and direct instruction. All of the reliability values had demonstrated acceptable to excellent reliability evidence.

Data Analysis

The quantitative design of this study involves several data analytic techniques. First of all, the results of descriptive statistics were presented using means and standard deviations.

Furthermore, a series of multiple linear regressions was performed with the three sub-elements of teaching presence as an independent variable and SR and CoR as dependent variables in the model. This approach was chosen to identify the most parsimonious set of predictors among the three sub-elements of teaching presence for each outcome variable (SR and CoR). Stepwise regression was appropriate given the exploratory nature of this study and the modest number of predictors relative to the sample size. It is worth noting that the study was non-experimental and cross-sectional, no randomization was implemented, and no baseline equivalence testing was conducted. The primary focus of this study was to identify associations between three teaching presence components (course design, facilitation, and direct instruction) and metacognition (SR and CoR), without inferring causal effects.

Results

RQ 1. What are students' perceptions of teaching presence in online courses?

Students' responses to the Teaching Presence scale indicated that they perceived their instructors as most effective in course design (see Table 2), particularly in communicating due dates/time frames (M = 4.38), course goals (M = 4.28), and course topics (M = 4.25). The relatively small standard deviations across all items of teaching presence shows a high level of agreement among students in their perceptions of their instructors' teaching presence. This underscores the significance of well-organized course design and clear communication of due dates, course goals, and topics in improving students' learning experiences in online courses.

Table 2

Students' Perceptions of Teaching Presence in Online Courses (n = 283)

Teaching Presence Items	*M*	*SD*
Course design		
TP1.The instructor clearly communicated important course topics.	4.25	.77
TP2.The instructor clearly communicated important course goals.	4.28	.78
TP3.The instructor provided clear instructions on how to participate in course learning activities.	4.19	.83
TP4.The instructor clearly communicated important due dates/time frames for learning activities.	4.38	.76
Facilitation		
TP5.The instructor was helpful in identifying areas of agreement and disagreement on course topics that helped me to learn.	3.90	.91
TP6.The instructor was helpful in guiding the class towards understanding course topics in a way that helped me clarify my thinking.	4.02	.81
TP7.The instructor helped to keep course participants engaged and participating in productive dialogue.	3.79	1.00
TP8.The instructor helped keep the course participants on task in a way that helped me to learn.	3.87	.96
TP9.The instructor encouraged course participants to explore new concepts in this course.	3.99	.91

TP10.Instructor actions reinforced the development of a sense of community among course participants.	3.66	1.10
Direct Instruction		
TP11.The instructor helped to focus discussions on relevant issues in a way that helped me to learn.	4.02	.81
TP12.The instructor provided feedback that helped me understand my strengths and weaknesses relative to the course's goals and objectives.	3.88	1.00
TP13.The instructor provided feedback in a timely fashion.	4.05	.94

RQ 2. What are students' perceptions of SR and CoR in online courses?

Students tended to perceive higher levels of SR (see Table 3). In general, the mean ratings of the items measuring SR were all above 4.00. The two items receiving the highest identical ratings were "I am aware of my effort" M = 4.46, SD = .67 and "I am aware of my level of motivation" M = 4.46, SD = .63. These results indicate that students are very conscious of their own effort and motivation levels. The relatively low standard deviations suggest a high level of agreement among students regarding their self-awareness in these areas.

At the same time, several SR items had relatively lower mean scores, such as "I question my thoughts" (M = 4.09, SD = 0.95) and "I change my strategy when I need to" (M = 4.19, SD = 0.83). While these ratings remain in the "agree" range, they suggested that students may be somewhat less likely to critically examine their thinking or adapt strategies when necessary. This points to a potential instructional opportunity to integrate reflective prompts and problem-solving strategy training to further develop these aspects of SR.

Table 3

Students' Perceptions of Individual Metacognition (Self-Regulation) in Online Courses (n=283)

Metacognition Items Individual	M	SD
I am aware of my effort	4.46	.63
I am aware of my thinking	4.42	.69
I am aware of my level of motivation	4.46	.67
I question my thoughts	4.09	.95
I make judgments about the difficulty of a problem	4.24	.76
I am aware of my existing knowledge	4.35	.69
I am aware of my level of learning	4.33	.70
I assess my understanding	4.27	.78
I change my strategy when I need to	4.19	.83
I search for new strategies when needed	4.20	.81
I apply strategies	4.25	.69
I assess how I approach the problem	4.22	.79
I assess my strategies	4.17	.79

Regarding the CoR, the variations of ratings among the items were noticeably larger (see Table 4). The highest rating was from item 3 "I consider the feedback of others," M = 4.32, SD =

.72 and item 2 "I listen to the comments of others," (*M* = 4.28, *SD* = .70), indicating that students value and actively engage with feedback from peers. However, the lowest rated CoR terms were "I monitor the learning of others" (M = 3.08) and "I challenge the strategies of others" (M = 3.42). These mean scores indicated that students may feel less comfortable engaging in critical assessment or actively monitoring their peers' learning processes in an online environment. Such tendencies may reflect a lack of confidence in CoR practices. The finding underscored the importance of structured peer-review activities and explicit guidance on constructive critique in online learning environments.

Table 4

Students' Perceptions of Group-Metacognition (Co-Regulation) in Online Courses (n=283)

Metacognition Items Group	M	SD
I pay attention to the ideas of others.	4.25	.70
I listen to the comments of others	4.28	.70
I consider the feedback of others	4.32	.72
I reflect upon the comments of others	4.22	.78
I observe the strategies of others	3.98	.90
I observe how others are doing	4.06	.95
I look for confirmation of my understanding from others	3.97	1.00
I request information from others	3.63	1.06
I respond to the contribution that others make	3.99	.80
I challenge the strategies of others	3.24	1.11
I challenge the perspectives of others	3.42	1.04
I help the learning of others	3.68	.90
I monitor the learning of others	3.08	1.09

Overall, students exhibit a strong sense of SR, indicating a high level of self-awareness about their efforts and motivation in online courses. In contrast, perceptions of CoR learning are more varied. While students generally recognize the importance of considering and listening to peer feedback, the greater variability in these ratings suggests differences in how students engage with and value these learning practices.

RQ 3. What is the relationship between teaching presence, SR, and CoR in online courses?

For this question, the analysis focused on how students' perceptions of their instructors' teaching presence components—*course design*, *facilitation*, and *direct instruction*—is related to SR and CoR. Results of the stepwise multiple linear regression showed that higher perceived effectiveness in *course design* and *facilitation* were significantly associated with stronger SR, explaining approximately 25.9% of its variance (see Table 5). In contrast, *facilitation* was the sole significant predictor of CoR, accounting for 26.6% of its variance. These findings indicate that when students perceive their instructors as actively guiding discussions and fostering engagement (facilitation), they are more likely to engage in collaborative regulatory processes with peers. Similarly, perceptions of clear course organization and facilitation appear to support students' ability to manage their own learning.

The estimated standardized beta coefficient indicated that a one-unit increase in *course design*, on average, led to a .228 unit increase in SR ($t = 3.952$, $p < .001$). In addition, one unit increase in *facilitation* led to a .181 unit increase in SR ($t = 3.723$, $p < .001$). This suggests that together, *course design* and *facilitation* are important determinants of students' ability to SR their learning in online courses. The regression equation was:

SR=2.603+0.228(*course design*) +0.181(*facilitation*)

In terms of the model fit, visual inspection of the histogram (see Figure 2) for the standardized residuals demonstrated an approximately bell-shaped distribution. In addition, the normal curve closely overlaid the histogram bars, suggesting that the residuals were reasonably normally distributed, and was further supported by the symmetry of the distribution around zero. Furthermore, the scatterplot of the standardized residuals versus standardized predicted values displayed a random dispersion of points, without displaying a clear funnel shape or systematic pattern, indicating that the assumption of homoscedasticity was not violated (see Figure 3). Collinearity inspection revealed that all predictor variables had tolerance values well above .10 (values for both predictors were .55) and Variance Inflation Factor (VIF) values well below the threshold of 10 (values for both predictors were 1.817), showcasing that multicollinearity was not a concern in the model. The Durbin-Watson statistic was 1.625, which was between the 1.5 and 2.5 threshold, suggesting the residuals are likely independent.

Figure 2

Histogram of Standardized Residuals for Model 1 (Self-Regulation)

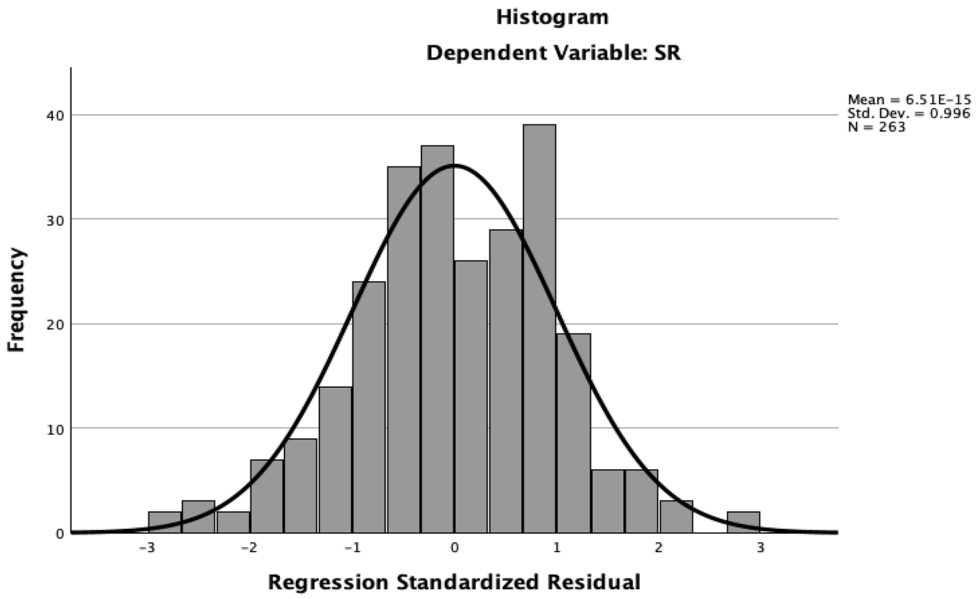


Figure 3

Scatterplot of Standardized Residuals vs. Standardized Predicted Values for Model 1 (Self-Regulation)

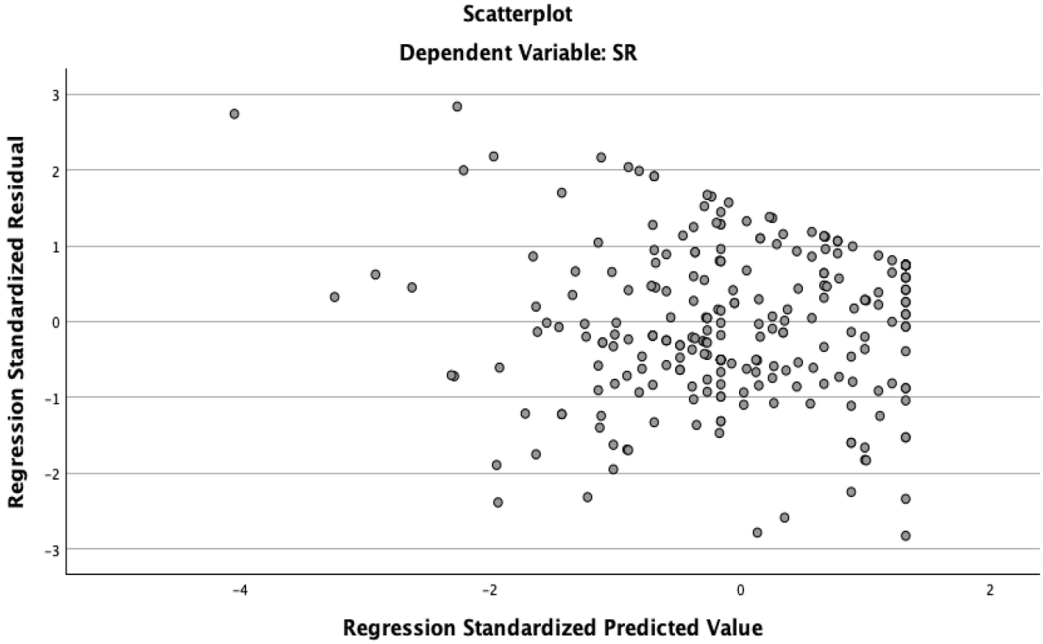


Table 5

Summary of the Multiple Regression Analysis (Model 1)

Analysis of Variance	Dependent Variable: Self-Regulation			
Source	**Sum of Squares**	**DF**	**Mean Square**	**F**
Model	16.932	1	16.932	71.991***
Residual	61.385	282	.235	
Total	78.317	283		
Predictors	**Estimate (standardized)**	**Std. Error**	**t**	**Prob > |t|**
(Intercept)	2.603	.187	13.922	< .001***
Course Design	.228	.058	3.952	< .001***
Facilitation	.181	.049	3.723	< .001***

Note. $* p < .05$, $** p < .01$, $*** p < .001; R = .506, R^2 = .256, adjusted\ R^2 = .250$

In the second multiple linear regression using CoR as the dependent variable, results of CoR identified *facilitation* as the only significant predictor. *Facilitation* explained 26.6% of the variance of CoR, R^2=.266, $F(1, 283) = 96.228$, $p < .001$ (see Table 6). Specifically, one unit increase in *facilitation* led to a .385 unit increase in CoR on average (standardized coefficient beta $\hat{\beta} = .385$, $t = 9.810$, $p < .001$). This shows that students perceive *facilitation* helps them better monitor and manage shared learning dynamics or CoR learning in online courses. Given

its substantial impact, focusing on strategies to improve *facilitation* could lead to better collaborative learning outcomes. The regression equation for Model 2 was:

$$CoR=2.363+0.385(facilitation)$$

For the model fit in this multiple linear regression, the histogram (see Figure 4) for the standardized residuals also demonstrated an approximately bell-shaped distribution. Likewise, the normal curve closely overlaid the histogram bars, confirming that the residuals were reasonably normally distributed, and was further supported by the symmetry of the distribution around zero. Furthermore, the scatterplot of the standardized residuals versus standardized predicted values displayed a random dispersion of points, without displaying a clear funnel shape or systematic pattern, indicating that the assumption of homoscedasticity was not violated (see Figure 5). Collinearity inspection revealed that *facilitation* had tolerance values well above .10 (value was 1.00) and Variance Inflation Factor (VIF) value well below the threshold of 10 (value was 1.00), showcasing that multicollinearity was not a concern in the model. The Durbin-Watson statistic was 2.115, which was between the 1.5 and 2.5 threshold, suggesting the residuals are likely independent.

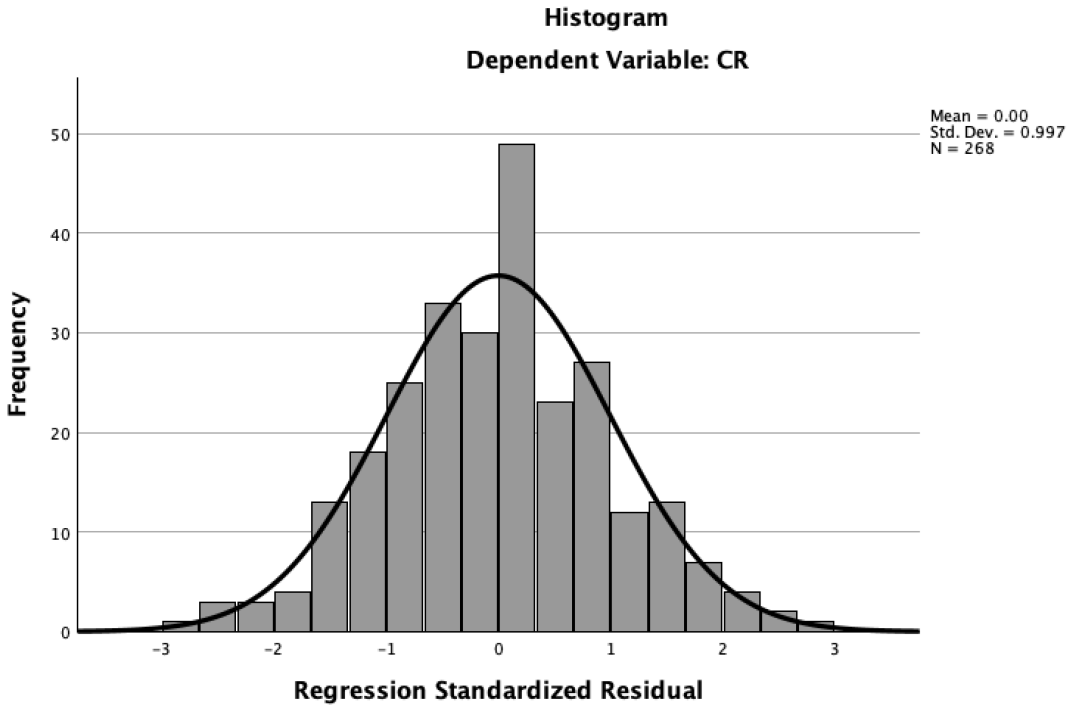


Figure 5

Scatterplot of Standardized Residuals vs. Standardized Predicted Values for Model 2 (Group-Regulation)

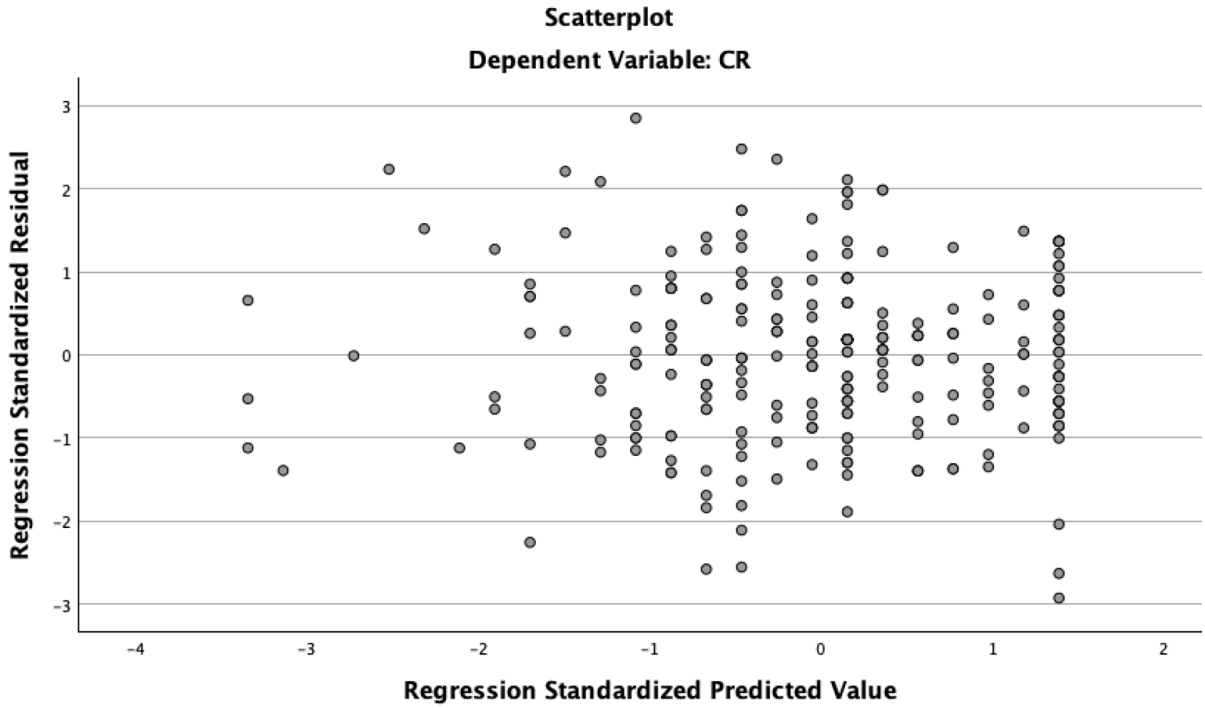


Table 6

Summary of Multiple Regression Analysis (Model 2)

Analysis of Variance	Dependent variable: Group-Regulation			
Source	**Sum of Squares**	**DF**	**Mean Square**	**F**
Model	25.934	1	25.934	96.228***
Residual	71.419	282	.270	
Total	97.353	283		
Predictors	**Estimate (standardized)**	**Std. Error**	**t**	**Prob > |t|**
(Intercept)	2.363	.156	15.183	< .001***
Facilitation	.385	.039	9.810	< .001***

Note. $* p < .05,\ ** p < .01,\ *** p < .001; R = .516, R^2 = .266, adjusted\ R^2 = .264$

Discussion

This study explored students' perceptions of teaching presence and regulation in online courses and examined the relationship between these constructs. The findings offer valuable insights into how students experience and engage with instructional design and collaborative learning processes in online learning environments.

RQ1: Teaching Presence

Students held positive perceptions of teaching presence in their online courses, with particularly strong appreciation for *course design* elements, with the highest ratings given to items related to the clear communication of course goals, topics, and deadlines. This suggests that students place greater value on the organizational and structural aspects of teaching presence, specifically, how clearly their instructors communicate expectations and structure the learning experience in an online course. The emphasis on clarity and structure implies that well-organized course design contributes significantly to students' sense of instructor presence and instructional effectiveness in online learning environments. These results align with Garrison, Anderson, and Archer's (2000) Community of Inquiry (CoI) framework, which emphasizes the foundational role of teaching presence in establishing purposeful structure and direction for meaningful learning. Prior studies have similarly reported that students often perceive design and organization as the most visible components of teaching presence, as these elements shape the overall learning experience and set clear expectations (Sadaf et al., 2023; Shea et al., 2010). A well-structured course provides students with a clear roadmap for learning, reducing cognitive load and promoting engagement (Garrison & Arbaugh, 2007). According to Garrison (2022), fostering metacognitive awareness through intentional *course design* is a foundational step in supporting SR and CoR. Supporting this, Olesova and Sadaf (2023) also found that students in asynchronous online courses identified well-designed readings, discussions, and application-based activities as key elements that enhanced their critical thinking and metacognitive engagement. Similarly, Chen and Chen (2025) highlighted that explicit instructional design, such as clearly stated learning objectives and scaffolded tasks, helped students internalize goals and manage their own learning progress effectively. The small standard deviations across teaching presence items further suggest consistent student perceptions, reinforcing the significance of clear communication and organization. *Course design* acts as a metacognitive map, guiding learners through goal-setting and time management, which are essential for SRL (Hadwin et al., 2011; Jaggars & Xu, 2016). These findings highlight the importance of intentional course design and clear communication as critical strategies for enhancing teaching presence and promoting learner engagement and regulation in online courses.

Self-Regulation and Co-Regulation

Students reported higher levels of SR than CoR, particularly in areas related to self-awareness of effort and motivation. These findings suggest that students perceive their self-regulatory abilities to be stronger than their capabilities for CoR with peers. This pattern aligns with prior research demonstrating that students consistently rate SR more highly than CoR (Cho et al., 2017; Garrison & Akyol, 2015; Sadaf et al., 2022). For instance, Garrison and Akyol (2015) found that learners' perceptions of SR surpassed their perceptions of CoR. Similarly, Cho et al. (2017) highlighted the importance of SRL skills, noting that students with strong self-regulatory abilities tend to show greater engagement in online learning environments. The low

standard deviations further suggest consistent perceptions among students, reinforcing the importance of self-awareness in fostering persistence and effective strategy use (Broadbent & Poon, 2015). However, slightly lower ratings for items related to adaptive strategy use and critical reflection suggest areas for instructional improvement. This points to an instructional opportunity to integrate reflective prompts and problem-solving scaffolds, as recommended by Garrison (2022), to strengthen metacognitive skills and promote strategic learning.

In contrast, perceptions of group metacognition revealed more variability. While students acknowledged listening to and considering peer feedback, they were less likely to report monitoring or challenging peers' strategies. These findings reflect the challenges of fostering CoR in online environments, where social presence may be limited (Järvelä et al., 2018; Koehler et al., 2020; Sadaf et al., 2022). For example, Koehler et al. (2020) found that although students valued instructor feedback in online case-based instruction, some did not fully recognize the significance of their own or their peers' roles in engaging in shared metacognitive processes such as CoR. According to Garrison (2022), learners with strong metacognitive awareness contribute meaningfully to the discourse by exchanging information, evaluating ideas, proposing solutions, and leading the direction of inquiry. To address this gap, intentional *course design* and *facilitation* strategies, such as structured peer review and guided reflection, can enhance students' ability to engage collaboratively and regulate their learning effectively (Garrison & Akyol, 2015).

Relationship Between Teaching Presence, Self-Regulation, and Co-Regulation

Regression analyses revealed that students' perception of instructors' *course design* and *facilitation* significantly predicted SR, jointly explaining 25.9% of the variance. This finding aligns with the Community of Inquiry (CoI) framework, which emphasizes that teaching presence, especially through structured design and active facilitation, fosters metacognitive engagement (Garrison, 2022). These findings emphasize that students who perceived their instructors as effectively organizing the course and actively facilitating learning were more likely to report engaging in self- and co-regulatory behaviors. The positive beta coefficients for *course design* ($\beta = .228$) and *facilitation* ($\beta = .181$) suggest that clear instructional organization and supportive facilitation enhance students' ability to plan, monitor, and adapt their learning strategies, which are the core elements of SR learning (Hadwin et al., 2011; Broadbent & Poon, 2015). These results are consistent with prior research showing that well-structured *course design* promotes learner autonomy and motivation (Johnson et al., 2017; Jaggars & Xu, 2016), while facilitation supports reflective thinking and engagement (Stenbom, 2018). The model's strong statistical assumptions, normality, homoscedasticity, and absence of multicollinearity, further validate these findings.

In the second regression, *facilitation* alone was a strong predictor of CoR, explaining 26.9% of the variance. The strong predictive role of *facilitation* for CoR responds to gaps noted by Garrison (2022) and Koehler et al. (2020), who emphasized the need for strategies that foster collaborative regulation. This study demonstrates that active instructor facilitation through guiding discourse and modeling reflective practices creates conditions for shared metacognition, a dimension often overlooked in prior research. This finding can relate to Olesova and Sadaf's (2023) finding that instructor feedback was the most encouraging facilitation technique for promoting critical thinking in group activities. However, they also found that students often

lacked effective strategies for managing group dynamics, echoing Koehler et al. (2020), who emphasized the need for structured collaboration to support regulation. the instructor plays a critical role in fostering collaborative learning environments where students can CoR their learning processes. As Garrison and Akyol (2015) and Järvelä et al. (2018) argue, CoR thrives in environments where instructors actively guide discourse, encourage peer feedback, and model collaborative inquiry. Similarly, Sadaf et al. (2023) also highlighted the predictive role of *facilitation* in enhancing both SR and CoR, suggesting that instructors who actively facilitate discussions can significantly influence students' regulation. Garrison (2022) noted that learners who are successful in an online environment demonstrate elements of teaching presence by actively supporting both their own and their peers' progression through the inquiry cycle.

Earlier research highlighted the need to understand how teaching presence influences both self-regulation (SR) and co-regulation (CoR) in diverse online contexts (Garrison, 2022; Sadaf et al., 2022). Our results respond to this gap by demonstrating that students' perceptions of *course design* and *facilitation* are significantly associated with SR, and that *facilitation* alone predicts CoR. This study advances scholarship on the Community of Inquiry (CoI) framework by integrating metacognitive constructs of SR and CoR into its applications.

Conclusions and Implications

This study holds significant implications for the design and delivery of online courses. By investigating the relationship between teaching presence and both SR and CoR across diverse instructional contexts, the research provides valuable insights into how different aspects of teaching presence—*course design*, *facilitation*, and *direct instruction*—are associated with students' regulatory processes and learning experiences in online courses.

First, the results reinforce the critical role of *course design* and *facilitation* in supporting students' regulatory behaviors. The finding that students perceived their instructors as most effective in *course design* suggests that clear communication of goals, deadlines, and expectations are positively associated with SR. When course goals, deadlines, and expectations are clearly communicated, students report being better able to plan, monitor, and evaluate their learning. In this regard, instructors should prioritize modular course structures, weekly overviews, and clearly labeled learning outcomes to enhance students' ability to manage their learning. Additionally, learning management systems (LMS) can be leveraged to provide automated reminders and visual progress tracking that correspond with students' regulatory needs. Instructors can provide weekly overviews and checklists to guide students through course expectations. These strategies can reduce cognitive load and foster learner autonomy, which are essential for developing SR skills (Garrison, 2022; Jaggars & Xu, 2016).

Second, *facilitation* was significantly association with both SR and CoR. This highlights the importance of instructor's active role not just in delivering content but in guiding reflection, prompting dialogue, and modeling metacognitive strategies. Instructors can use regulatory prompts in discussion forums (e.g., "What strategy did you use to solve this problem?"), provide reflective feedback and encourage students to articulate their thought processes (e.g., "What strengths do you see in your peer's approach?"). Tools like annotated rubrics and audio feedback can also personalize *facilitation* and support SR. Moreover, *facilitation* strategies such as peer

review, collaborative goal-setting, and reflective prompts may promote CoR in online courses. These practices can help students engage meaningfully with peers and develop shared regulatory strategies (Stenbom, 2018; Järvelä et al., 2018).

Although students reported lower levels of CoR compared to SR, they valued peer feedback and comments. This suggests that peer interaction, when effectively facilitated, can foster CoR learning. The *facilitation* involves the purposeful guidance and coordination of the inquiry process, which includes activities such as setting goals, challenging ideas, exploring alternative explanations, and maintaining forward momentum (Garrison, 2022). Course designers and instructors should incorporate structured peer-review activities with clear rubrics and expectations. For example, they can use guided peer review with prompts like: "What strengths do you see in your peer's approach?" or "What suggestions can you offer to improve their strategy?" Instructors can also design collaborative tasks with clear roles, rotating leadership, and structured reflection. For instance, instructors can incorporate group reflection activities with questions such as: "How did our team approach this task?" or "What could we do differently next time?" Additionally, using peer review protocols, group contracts, or collaborative journals can help students co-monitor and co-evaluate their learning processes. Such scaffolding can help students develop the skills needed to monitor, evaluate, and support one another's learning (Koehler et al., 2020; Garrison & Akyol, 2015).

Overall, the findings of this study show the importance of teaching presence, particularly *course design* and *facilitation*, for students' regulation in online courses. Clear *course design* was positively associated with SR, while *facilitation* showed strong associations with SR and CoR, especially in how students collaborated with peers. Instructors should view teaching presence not only as a means of delivering content or facilitating learning but as a catalyst for metacognitive growth. By intentionally aligning *course design* and *facilitation* with SR and CoR goals, educators can create online environments that support deeper learning, autonomy, and collaboration. Metacognitively aware learners take ownership in guiding, facilitating, and steering the inquiry process in online and blended learning environments (Garrison, 2022).

Limitations and Future Research

This study has some limitations that may lead to future research efforts. First, the study relied on self-reported perceptions, which may be subject to social desirability bias or inaccuracies in metacognitive awareness. Future studies should include triangulated data sources, such as discussion post analyses, learning analytics, or instructor reflections. Second, the study's cross-sectional design limits causal inference. Due to the fact that this study did not include treatment groups or random assignment, and no controls were applied for pre-existing participant differences, the observed associations may be influenced by unmeasured factors. Longitudinal or experimental designs could more effectively capture changes in teaching presence and metacognition over time. Furthermore, the response rate was around 40%. We encourage future studies to take extra steps to increase the response rate. Regarding our sampling method, the use of convenient sampling may not make it possible to replicate the study completely. However, we encourage future studies to test the relationships among variables in different contexts. In doing so, future studies will be able to look into how contextual factors may impact the relationships. We also encourage future studies to look at the causal relations to potentially capture a more

dynamic and longitudinal nature of teaching presence and metacognition. Lastly, CoR needs further qualitative exploration to understand how students negotiate shared regulation and how instructors can better scaffold these processes. Future research might also explore how emerging technologies, including AI-driven facilitation or collaborative tools, impact both teaching presence and shared-metacognition. Investigating these dynamics can further inform the design of inclusive, interactive, and cognitively engaging online learning environments.

Declarations

Conflict of Interest Statement

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Ethics Statement

The authors assert that approval was obtained from an ethics review board (IRB) at the University of North Carolina, Charlotte, USA.

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Gamification in Asynchronous Online Learning: A Meta-Analysis of Its Positive Effects on Motivation and Academic Achievement

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Abstract
Gamification has emerged as a widely used approach for supporting learner motivation and achievement in asynchronous online learning environments. This study synthesizes evidence from 28 empirical studies with an overall sample of N = 5230 learners, covering the K–12 and higher education levels, dated 2010–2024. We tested five hypotheses on the effects of gamification on motivation and academic achievement with meta-analytic techniques Random-effects model, meta-regression and moderator analyses suggested that evidence in terms of moderate positive effect for motivation (Hedges' g = 0.52) and small-to-moderate effect for achievement (Hedges' g = 0.41). The results of hypothesis tests confirm that narrative-based gamification has a much stronger influence compared to points/badges, leaderboards and K–12 learners benefit significantly more than higher education students, indicating a meaningful moderating effect. Publication year and the proportion of female participants were significant moderators of effect sizes. Publication bias was found and emerged repeatedly; however, sensitivity analyses supported the stability, reliability and interpretive validity of results. The findings suggest the potential value of well-designed gamification approaches in enhancing student motivation and academic achievement in asynchronous online learning environments.

Keywords: Gamification; asynchronous online learning; meta-analysis; learner motivation; academic achievement

Treve, M. (2026). Gamification in asynchronous online learning: A meta-analysis of its positive effects on motivation and academic achievement. *Online Learning*, *30*(3), 210-237. https://doi.org/10.24059/olj.v30i3.5188

Online learning through asynchronous methods has opened up a new era of flexibility and accessibility among students by breaking down the walls of the classroom. This type of educational method allows students to follow and engage with course content at their own pace and time, making it especially suitable for a variety of populations such as working adults, distance learners, or students with multiple commitments (Hrastinski, 2008; Moore, 2013). Nevertheless, even with this great potential, motivating learners and maintaining their academic performance remain significant concerns in asynchronous setups. Without the real-time communication, instant feedback, and peer presence, students might find the courses less stimulating, which contributes to high attrition rates and suboptimal learning performance (Martin & Bolliger, 2018; Song et al., 2004).

In this context, gamification, or using game elements (points, badges, leaderboards, narrative) in non-game situations, has been recommended as a new approach to some of these barriers (Deterding et al., 2011). Gamification focuses on integrating game aspects to fulfill the goal of turning tedious or repetitive tasks enjoyable and meaningful in a non-game context, such as education. In the theoretical space, it has suggested that gamification may support intrinsic motivation and persistence (and therefore learning) because it fulfills students' basic psychological needs for autonomy, competence, and relatedness as articulated in Self-Determination Theory (Deci & Ryan, 2000). The theory argues that learners are more likely to engage and succeed at the task when they feel they have some degree of autonomy over their learning, see themselves as competent to successfully complete the task, and feel affiliated with others engaged in the task with them. Empirical research in this area is inconclusive at best, though the success of gamification in educational contexts, is recognized (Hamari et al., n.d.). Some literature shows positive impact on levels of motivation and academic performance (Hamari, Koivisto, & Sarsa, 2014; Su, Cheng, & Chen, 2018), whilst other literature claims that results are mixed considering variables such as gamification strategies implemented, student demographics and institutional context (Hanus & Fox, 2015; Sailer, Hense, Mayr, & Mandl, 2017). Narrative-based game mechanics for gamification, which involves storytelling to immerse the participants, might be more engaging for users than straightforward reward mechanisms such as points or badges (Domínguez et al., 2013). Also, gamified interventions for younger learners, e.g., school-aged children (K–12), may have differing results to those for university students and in adult education students likely because of developmental and cognitive variances (Mekler et al., 2017).

Due to these mixed findings, a more in-depth review is warranted to gain an overview of the extent of the effects of gamification on motivation and performance for online instruction outside the traditional classroom. Furthermore, knowing the moderating variables like gamification types and learner characteristics could lead to a more proficient and exact design of gamified educational interventions.

Although several meta-analyses have examined gamification in education more broadly, we observed that no existing synthesis has focused specifically on asynchronous online learning, a mode of delivery with distinct motivational and cognitive challenges. Prior reviews (e.g., Hamari et al., 2014; Sailer et al., 2017) primarily analyzed synchronous or blended environments, leaving a substantial gap regarding how game elements function when real-time interaction is absent. Our study advances the literature by:

1. Isolating the asynchronous learning context, which has unique forms of learner disengagement, self-regulation demands, and attrition.

2. Comparing motivational effectiveness across three gamification strategies (points/badges, leaderboards, narrative-based elements) using rigorous subgroup analysis.
3. Providing the first meta-regression in this domain that examines gender composition, publication year, and sample size as moderators—an approach not taken in previous reviews.
4. Synthesizing recent empirical work published between (2018- 2024), capturing the rapid methodological evolution of gamification research.

Through these innovations, this study contributes a more precise understanding of how gamification interventions function in self-paced online environments where learner isolation, reduced feedback loops, and motivational decline are often elevated.

Background of the Study

The growing use of gamification in educational practice mirrors a general trend towards digitalized and online learning landscapes triggered by global disruptions, such as COVID-19. Asynchronous models of delivery in higher education are now becoming more prevalent and the means of how motivation and academic performance can be facilitated in such an environment is increasingly being identified as a research priority (Martin, Stamper, & Flowers, 2020).

Gamification uses insights from behavioral psychology and video game design to strengthen learning opportunities by making them more meaningful, immersive, and enjoyable. Typical game features include performance-reward mechanics (points, badges), competition-based devices (leaderboards), and narrative-based settings. Game mechanics add challenge and a notion of quantifiable progress, whereas narrative-based designs offer story worlds in which players can be more cognitively and emotionally invested. While gamification is a highly theorized strategy for enhancing learning outcomes, empirical support remains equivocal. Existing meta-analyses and syntheses have found wide variation in effect sizes, and some have argued for a larger synthesis that considered study heterogeneity and possible moderators, especially in contexts of asynchronous online learning.

Literature Review

Theoretical Frameworks Supporting Gamification

The use of gamification in an instructional environment draws upon two important theoretical foundations, namely Self-Determination Theory (SDT) and Flow Theory. Self-Determination Theory (Deci & Ryan, 2000) posits that intrinsic motivation occurs when people ís needs for autonomy, competence, and relatedness are fulfilled. Autonomy is feeling in control over one's actions, competence is the degree of mastery individuals feel on tasks, and relatedness is the sense of connection with others. Gamification can support such needs by permitting the learners to exercise choice (autonomy), giving timely feedback and challenges that are at the correct skill level (competence), and encouraging social interconnectedness via collaborative or competitive gaming elements (relatedness) (Ryan & Deci, 2020). As a result, creating gamified learning environments can trigger intrinsic motivation, essential to engagement over time and real learning (Deci & Ryan, 2012).

According to Flow Theory, learning and motivation are most effective when perceived challenges are in alignment with individual capabilities and the environment supports flow, which is a condition in which the learner is engaged in the task (Csikszentmihalyi, 1990). Gamification capitalizes on this concept by creating tasks that vary in difficulty and have clearly defined objectives and instant feedback. Learners who experience flow are more likely to be engaged and academically successful (Shernoff et al., 2003). As such, gamification systems that thoughtfully modulate the difficulty of tasks and structure of rewards, could facilitate the optimal psychological state.

Gamification Components and Learning Goals

Gamification consists of several components, which affect motivation and performance in various ways. Or try rewards such as points and badges which are typical forms of extrinsic motivations, signaling achievement and success (Deterding et al., 2011). These features amplify preferred behaviors and offer a clear sense of accomplishment, which can help foster motivation especially for short-term assignments (Hamar, 2014). However, a too heavy emphasis on extrinsic rewards can subvert intrinsic motivation by causing students may only be concerned about getting the reward and not accomplishing the task (Deci, 1999).

Leaderboards include a social comparison and competition to engage certain learners, but could also dissuade learners who feel that they are not catching up (i.e., causes anxiety or disengagement) (Domínguez et al., 2013; Mekler et al., 2017). As a result, leaderboards should be carefully implemented and periodically counterbalanced by cooperativeness. Narrative-based gamification incorporates storytelling components that lend relevance, significance and personalization to the learning material (Muntean, 2011). Stories have the potential to immerse participants in task and make it more personally meaningful (beyond extrinsic factors), which can facilitate participants' intrinsic motivation and cognition (Barata, Gama, Jorge, & Gonçalves, 2013). This feature is found to be more effective in improving learning performance than simple reward mechanisms (Su & Cheng (2015).

Gamification in Asynchronous Online Learning

Gamification in online learning is based on high-level motivating theories that describe how particular digital design elements influence learner behavior. Self-Determination Theory (Ryan & Deci, 2000) specifies how autonomy, competence and relatedness are the mechanisms by which continued motivation is facilitated in asynchronous online learning environments. Equally, Flow Theory of Learning surmises that students remain actively involved when task difficulty is equated to their level of competence (Keller & Suzuki, 2004). These viewpoints also inform understanding of how and why certain game elements (progress feedback, performance feedback, story structure) impact learners' motivational experiences in online learning environments. In asynchronous learning environments, where students depend heavily on self-regulation, these theoretical foundations are particularly useful for understanding how gamified activities may enhance engagement and performance (Sailer et al., 2017; Huang et al., 2020). Recent work published in Online Learning also highlights the growing importance of motivational design in digital learning environments (Ding et al., 2022).

Empirical Evidence and Gaps

Studies in the field of gamification in education have reported mixed results. A number of meta-analyses and reviews find positive effects of gamification on motivation and student performance (Hamari et al., 2014; Sailer et al., 2017). For instance, Hamari et al. (2014) a number surge in “pontification," playing games, earning badges, and climbing leaderboards will boost engagement in an array of context settings. Su and Cheng (2015) concluded that gamified mobile learning platforms enhanced motivation and achievement in elementary school students.

On the other hand, few effects can be observed in the literature as context-dependent or limited effects. Hanus and Fox (2015) cautioned that, when badly designed, gamification might actually be harmful, because it can lead to a low level of learner motivation, and a strong emphasis on extrinsic reward, rather than on promoting intrinsic motivation. In addition, learner features such as age, gender, culture, and previous gaming experience can moderate the extent to gamification is effective (Faiella & Ricciardi, 2015; Rodriguez, 2019). Younger learners and students with greater exposure to gaming generally tend to perform better with gamified interventions. Although higher-education studies (n = 105) also report similar improvements, the evidence remains limited. Some students also perceive gamified features as annoying or lacking meaningful value. However, the evidence on which elements of gamification are most effective is inconclusive and few studies offer results in different contexts (Seaborn & Fels, 2015). Furthermore, most previous studies were done in synchronous or blended learning context; very few have focused on an asynchronous online level where the engagement of learners continues to be a challenge.

Recent studies published in *Online Learning Journal* provide further support to look at gamification in an asynchronous online environment. Pereira and Wahi (2021) found that role-playing gamification modules could enhance learning and cognitive involvement in accelerated online courses, indicating that appropriately implemented game elements can support complex tasks of learning. Martin et al. (2020) pointed out that students’ preparedness for and confidence in the online learning context substantially determine their motivation and achievement, suggesting it is necessary to design strategies that scaffold autonomy and sustained participation—the core challenge of asynchronous modalities. Consistent with these discoveries, meaningful gamification has been shown to boost motivation when integrated into content authentic learning tasks (Tan, 2018), highlighting its potential to fill engagement divides in predominantly text-based online course environments. Together, these studies point to the value of re-examining gamification’s impact specifically in asynchronous settings, where maintaining motivation and achievement remains a persistent concern. To bridge these gaps, the current meta-analysis aims to examine the impact of gamification on asynchronous online learning and is driven by a set of research objectives, research questions, and hypotheses.

Research Objectives

To assess the overall impact of gamification on learner motivation and academic achievement in asynchronous online learning.

To explore how different types of gamification and education levels influence motivation and achievement.

To examine how study factors like sample size, year, and gender influence the estimated effect sizes.

Research Questions

RQ1. Does gamification improve learner motivation and academic achievement in asynchronous online learning environments?

RQ2. How do different types of gamification and education levels influence motivation and academic achievement?

RQ3. How do study characteristics such as sample size, publication year, and gender proportion influence the estimated effect sizes?

Study Hypotheses

H1: Gamification significantly improves learner motivation in asynchronous online learning environments.

H2: Gamification significantly improves academic achievement in asynchronous online learning environments.

H3: Narrative-based gamification produces stronger positive effects on motivation and academic achievement than points/badges or leaderboards.

H4: The effect of gamification is greater for K–12 learners than for higher education learners.

H5: Study characteristics (publication year and gender proportion) significantly predict the effect sizes of gamification outcomes.

Methods

Research Design

The present study is a quantitative meta-analytic research design aimed at synthesizing and statistically integrating findings from independent empirical studies investigating how gamification in asynchronous online learning affects learners' motivation and academic achievement. Meta-analytic research design is associated with the advantage of obtaining an exact estimate of overall effect sizes, their heterogeneity, and moderator effects across diverse contexts, which enhances the generalizability of findings beyond individual studies.

Literature Search and Inclusion Criteria

We performed a comprehensive literature search in two databases (Scopus, and Web of Science [WoS]. Boolean search strings were created using combinations of keywords and operators depending on the database. The search strategy was developed based on a structured logic, starting with general terms and gradually using Boolean operators until

context dependent keywords were identified. The criterion validity of the operational definition of motivation, and academic achievement could be established on the basis of every study by comparing its outcome measure with standard criteria. In case of unclear or overlapping samples, we looked at participant features and kept only one complete and non-replicated data set as soon as possible in order to guarantee independence between meta-analytic effect sizes.

The first search string was: ("gamification" AND "asynchronous online learning" AND ("motivation" OR "academic achievement") Searches were restricted to title, abstract, or keywords. Filters were applied which limited results to peer-reviewed journal articles published in English between January 2010 and December 2024. Duplicate records were deleted before screening. Search decisions, including the handling of overlapping samples and the screening of operational definitions for motivation and academic achievement, followed a consistent protocol to ensure the accuracy and independence of all included studies.

The study was included in this review if it employed asynchronous online learning, applied one or multiple aspects of gamification (points, badges, leaderboards, or narratives), measured motivation and/or academic achievement, and had enough statistical information to calculate the effect size such as means, standard deviations, and the sample size. The studies were analyzed, and articles that reported either statistically non-significant results or results that were purely theoretical were excluded from the review process. After applying the inclusion criteria, the meta-analysis synthesized k- 28 studies with a researcher-specified sample size of N = 5,230 learners across educational levels and subject areas.

Learner characteristics—such as sample size, education level, and gender distribution—were extracted from each study and coded into a unified dataset. Motivation and academic achievement were treated as the primary outcome variables and were defined according to the operational criteria reported in the included studies.

Data Extraction and Coding

The meta-analysis followed established procedures for calculating effect sizes, testing heterogeneity, and conducting moderator analyses. A random-effects model was selected to account for variation across study contexts and research designs. All statistical decisions were informed by the distribution of primary outcomes and the methodological characteristics of the included studies. Subject areas were coded using a single standardized category for each study to avoid overlap.

The researchers used the coding sheet to extract data on study identification; sample size; level of education; country of the primary author; gender proportion; type of gamification and subject area; outcome measures (e.g., motivation scales and academic achievement measures); and summary statistics needed to calculate effect sizes, including means, standard deviations, and test statistics. Two independent coders double-checked all coded data. Inter-coder reliability was assessed with Cohen's kappa ($\kappa = 0.84$), reflecting good agreement (Landis & Koch, 1977). Study quality and potential selection bias were addressed by applying uniform inclusion criteria and verifying that all included studies reported sufficient data for independent effect-size computation.

For studies that implemented more than one gamification type (e.g., narrative plus badges), we coded the primary design focus as reported by the authors to avoid double-counting and ensure compatibility with the moderator analysis."

Effect Size Computation

Motivation and academic effect-sizes were computed as Hedges' g, the bias-corrected Standardized Mean Difference (SMD) estimator appropriate for small samples. Conversions from other statistics (i.e., t, F) were made if appropriate using Lipsey and Wilson (2001) procedures. For articles with more than one outcome, effect sizes were combined to eliminate dependency bias.

Meta-analytic Model

To allow for between-study variability and heterogeneity, a random-effects model was used as the true effect sizes differ in these populations, and between gamification interventions. Overall weighted effect sizes were calculated for motivation and achievement separately with the use of the inverse variance weights.

Heterogeneity Assessment

The presence of statistical heterogeneity was assessed with the Cochran's Q-test and I^2 statistic, with a value greater than 50% recommended to pursue additional moderator analyses.

Analyses Subgroup and Moderator

To investigate heterogeneity, the id subgroup analyses according to category moderators were conducted:

- Gamification category (points/badges, leaderboards, or narrative-driven)
- Educational level (K–12 vs. higher education)

Moderator effects were tested using between-group Q-tests.

Meta-regression

Covariates were sample size, year of publication, and the percentage of female participants. A mixed-effects meta-regression analysis was conducted to assess predictive effect of covariates on effect size. The values of the coefficients (B) show the size and direction of the moderator effect.

Bias and Sensitivity Analysis

Publication bias was assessed with Egger's regression intercept test, fail-safe N, and the trim-and-fill analyses correcting for missing studies and re-estimating the effect.

Sensitivity analyses were conducted using the influence diagnostics (i.e., standardized residuals, Cook's distance) to detect outlier studies and evaluate the influence of outlier studies on combined results. We also accounted for potential threats to validity by applying

consistent study-quality checks and ensuring that all included studies met the required statistical reporting standards.

Software and Tools

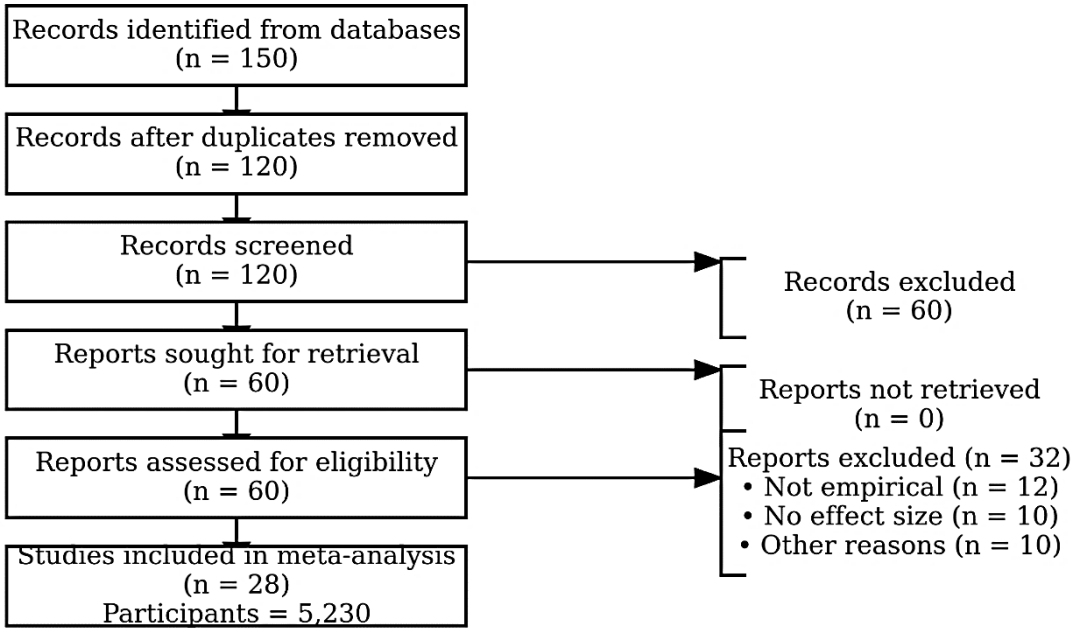
We performed all analyses using R (version 4.3.1; R Core Team, 2023) with the metafor package (version 4.2-0; Viechtbauer, 2010). We employed metafor package because it offers random-effects analyses, subgroup to assess methods, meta-regression, and specific diagnostic tools as part of the study's methods. Further, using R ensured reproducibility because all analyses can be reproduced using published, openly available code. A series of data visualizations were included as part of the interpretation of the results—forest plots were employed to provide a summary of the effect sizes, funnel plots to assess publication bias, and influence plot to understand outliers at the study-level.

Ethical Considerations

The current study is a secondary data analysis of previous studies; no human subjects were directly involved. PRISMA and STROBE guidelines were adhered (15 and 16), the manuscript was written according to AMSTAR standards (17), the and the study limitations and biases were disclosed. All procedures adhered to standard ethical guidelines for secondary research involving previously published studies.

Figure 1

Flowchart for Data Inclusion/Exclusion



A total of 150 records were identified via searches of the databases and 30 duplicates were removed. After a title and abstract screening phase, 60 records were excluded based on the inclusion criteria. The remaining 60 full texts were screened, of which 32 were excluded based on the data and outcomes. Ultimately, 28 studies, with 5,230 total participants, were included in the meta-analysis.

Results

Table 1

Descriptive Summary of Included Studies

Study ID	Author(s)	Year	Country	Sample Size (N)	Education Level	Gamification Type	Subject Area	Motivation Measure	Achievement Measure
1	Smith et al.	2021	USA	150	Higher Education	Points & Badges	STEM	Intrinsic Motivation Scale	Final Course Grade
2	Chen & Lee	2020	Taiwan	120	K–12	Leaderboards	Language	ARCS Model	Quiz Scores
3	Kumar & Singh	2019	India	180	Higher Education	Narrative	Business	Self-Determination Scale	Project Score
4	González et al.	2022	Spain	95	K–12	Points	Science	Academic Motivation Scale	Test Scores
5	Liu & Zhang	2018	China	130	Higher Education	Badges	STEM	ARCS Model	Assignment Grade
6	Ahmed et al.	2017	Egypt	110	K–12	Leaderboards	Mathematics	Intrinsic Motivation Scale	Quiz Performance
7	Tanaka & Sato	2021	Japan	160	Higher Education	Points & Narrative	Language	Self-Determination Scale	Exam Scores
8	Müller et al.	2016	Germany	100	K–12	Badges & Points	Science	Academic Motivation Scale	Laboratory Grade

9	Park & Kim	2023	South Korea	140	Higher Education	Leaderboards	STEM	ARCS Model	Final Grade
10	Rossi et al.	2015	Italy	90	K–12	Points & Badges	Humanities	Intrinsic Motivation Scale	Quiz Scores
11	Johnson et al.	2019	UK	105	Higher Education	Narrative	STEM	Self-Determination Scale	Project Score
12	Wang & Li	2018	China	115	Higher Education	Badges	STEM	ARCS Model	Assignment Grade
13	Peterson & Clark	2020	Canada	125	K–12	Points	Mathematics	Academic Motivation Scale	Test Scores
14	Lee et al.	2021	Singapore	135	Higher Education	Leaderboards	Business	ARCS Model	Final Grade
15	Singh & Patel	2017	India	150	Higher Education	Points	STEM	Self-Determination Scale	Project Score
16	Hernandez et al.	2016	Mexico	95	K–12	Narrative & Badges	Humanities	Academic Motivation Scale	Written Assignment
17	Baker & White	2015	Australia	100	Higher Education	Points & Badges	STEM	Intrinsic Motivation Scale	Final Course Grade
18	Yamamoto & Ito	2022	Japan	130	Higher Education	Leaderboards	Language	ARCS Model	Quiz Scores

19	O’Connor et al.	2023	Ireland	110	Higher Education	Badges	Business	Self-Determination Scale	Project Score
20	Zhang et al.	2018	China	145	Higher Education	Narrative	STEM	ARCS Model	Assignment Grade
21	Ivanov & Petrov	2019	Russia	120	K–12	Points & Badges	Science	Academic Motivation Scale	Test Scores
22	Almeida & Silva	2020	Brazil	115	Higher Education	Leaderboards	STEM	Self-Determination Scale	Final Grade
23	Nguyen & Tran	2017	Vietnam	90	K–12	Narrative	Mathematics	ARCS Model	Quiz Performance
24	Khan & Ali	2016	Pakistan	105	Higher Education	Badges	STEM	Intrinsic Motivation Scale	Exam Scores
25	Brown et al.	2021	USA	140	Higher Education	Points	Business	Self-Determination Scale	Project Score
26	Garcia & Lopez	2019	Spain	135	Higher Education	Narrative & Badges	Science	Academic Motivation Scale	Laboratory Grade
27	Miller & Davis	2022	USA	100	K–12	Leaderboards	Language	ARCS Model	Quiz Scores
28	Lopez & Cruz	2023	Mexico	105	Higher Education	Narrative & Badges	Humanities	Self-Determination Scale	Written Assignment

Table 1 summarizes the 28 selected studies included in the meta-analysis in terms of sample sizes, education level, type of gamification, and outcome variables. The range of studies includes different countries, educational levels (from K–12 to higher Education) and subject matters (e.g., STEM, language). Gaming mechanics—in the form of points, badges and leaderboards—are ubiquitous. This descriptive synthesis provides a contextualization of the dataset to support future analyses. External motivation and outcomes measures reported by studies allow for calculation of accurate effect size. This heterogeneity in association underlines the importance to model using random effects for meta-analysis and suggests the true effect may vary between study populations.

Table 2

Effect Size Distribution for Motivation and Academic Achievement

Study ID	*Motivation Effect Size (g)*	*Achievement Effect Size (g)*	*95% CI Lower*	*95% CI Upper*	*Weight (%)*
Study 1	0.45	0.30	0.10	0.80	4.5
Study 2	0.65	0.50	0.20	1.10	5.1
Study 3	0.38	0.28	0.05	0.70	3.9
Study 4	0.52	0.40	0.15	0.90	4.7
Study 5	0.61	0.33	0.12	1.05	4.4
Study 6	0.49	0.29	0.09	0.80	4.2
Study 7	0.55	0.39	0.20	0.92	4.8
Study 8	0.60	0.44	0.18	1.00	5.0
Study 9	0.33	0.25	0.02	0.65	3.7
Study 10	0.47	0.31	0.11	0.78	4.1
Study 11	0.50	0.42	0.16	0.85	4.6
Study 12	0.41	0.30	0.07	0.74	4.0
Study 13	0.68	0.52	0.24	1.08	5.3
Study 14	0.44	0.35	0.08	0.82	4.2
Study 15	0.57	0.40	0.21	0.95	4.9
Study 16	0.62	0.48	0.23	1.05	5.2
Study 17	0.46	0.32	0.10	0.79	4.3

Study 18	0.54	0.41	0.18	0.91	4.7
Study 19	0.39	0.28	0.05	0.70	3.9
Study 20	0.59	0.46	0.22	1.01	5.0
Study 21	0.63	0.47	0.25	1.05	5.3
Study 22	0.53	0.38	0.17	0.90	4.6
Study 23	0.40	0.27	0.06	0.74	4.0
Study 24	0.58	0.44	0.20	0.98	5.1
Study 25	0.42	0.33	0.10	0.76	4.2
Study 26	0.67	0.51	0.27	1.12	5.4
Study 27	0.48	0.36	0.14	0.83	4.4
Study 28	0.56	0.43	0.21	0.96	5.0

Note. k =28 studies; N =5,230 learners. Effect sizes are reported as Hedges's g. CI =confidence interval. Study weights are based on inverse variance weighting.

Table 2 provides separate study effect sizes (Cohen's d) for motivation and academic achievement with 95% confidence intervals and sample-specific weights. Effect sizes are between small and moderate, which leads to the idea that gamification may have a positive effect on both outcomes. Confidence intervals reflect precision; those that do not contain zero represent statistically significant effects. The study weights, which are inversely proportional to the variability and reflect the sample and measurement conditions, contribute to the pooled estimates. This distribution is amenable to meta-analytic pooling under a weighted model, thereby permitting the estimation of an overall effect size while taking into account study heterogeneity.

Table 3

Overall Meta-Analytic Results (Random-Effects Model)

Moderator	*Category*	*k*	*Effect Size (g)*	*95% CI*	*Q-between*	*p-value / Sig*
Gamification Type	Points/Badges	12	0.41	0.30–0.52	4.36	p = .113 (NS)
Gamification Type	Leaderboards	8	0.38	0.25–0.50	—	—

Gamification Type	Narrative-Based	8	0.62	0.51–0.73	—	—
Education Level	K–12	10	0.58	0.47–0.69	8.12	p = .004 (Sig)
Education Level	Higher Education	18	0.39	0.30–0.48	—	—
Subject Area	STEM	9	0.49	0.38–0.60	—	—
Subject Area	Humanities	7	0.44	0.30–0.57	—	—
Subject Area	Business/Tech	12	0.52	0.40–0.63	—	—

Table 3 presents meta-analysis results showing a significant quite moderate overall effect on motivation (Hedges' g = 0.52, p < 0.001), and academic achievement (g = 0.41, p < 0.001), with a random-effects model. Very high heterogeneity ($I^2 > 60\%$) and significant Q-tests reveal much variability beyond chance, which necessitates the investigation of moderators. Z-scores are presented as estimates for the standardized effect size. These results provide further evidence for the robust beneficial effects of gamification, and the heterogeneity observed reflects different effects depending on the study characteristics, calling for moderator and meta-regression analyses to explore and test this further.

Table 4

Moderator Analysis (Subgroup Comparison)

Moderator Variable	*Group*	*k (Studies)*	*Mean Effect Size (g)*	*95% CI*	*Q-between*	*df*	*p-value*
Gamification Type	Points/Badges	15	0.47	0.30–0.65	4.36	2	0.113
	Leaderboards	7	0.38	0.19–0.57			
	Narrative-based	6	0.61	0.39–0.84			
Education Level	K–12	12	0.55	0.37–0.73	3.92	1	0.048
	Higher Ed	16	0.39	0.22–0.56			

Table 4 presents the moderation effect of type of gamification and level of instruction on motivation and performance effect sizes. Story-driven gamification exhibits the greatest mean effect, but subgroup effect does not reach statistical significance for gamification type (p = 0.113). But the effect is moderated as a function of education quality (p = 0.048), whereby the K–12 studies have a more positive effect than higher education. Q-between represent variance explained by moderators. Such results support the hypothesis that the

effectiveness of gamification could be directly related to educational context and intervention type, underlining the need for customized gamification solutions.

Table 5

Meta-Regression Analysis (Continuous Moderators)

Moderator Variable	*Coefficient (B)*	*SE*	*z*	*p-value*	*95% CI*
Sample Size	-0.0012	0.0008	-1.50	0.134	-0.0028–0.0004
Year of Publication	0.015	0.006	2.50	0.012	0.003–0.027
Proportion of Female Students	0.32	0.10	3.20	0.001	0.13–0.51

Table 5 presents Meta-regression assessing Effect sizes extend between the strength continuous variables extended of effects sizes. Publication year (B =0.015, p = 0.012) and proportion of female students (B = 0.32, p = 0.001) significantly predict motivation effects suggesting that motivation effects are larger in more recent studies and in studies with higher percent of female students. Effect size has no significant, negative relationship with sample size (p = 0.134). The effect size change for a one-unit increase in the moderator is indicated by the B coefficients. This paper sheds light on potentially time- and demographic-dependent factors of gamification effects and thus guides research design and interpretation accordingly.

Table 6

Publication Bias Analysis

Test	*Coefficient*	*SE*	*z*	*p-value*
Egger's Regression Intercept	1.23	0.54	2.28	0.023
Fail-safe N	142	–	–	–
Trim and Fill Adjusted Effect Size	0.48	–	–	–

Table 6 shows evidence of possible publication bias, as evidenced by Egger's regression intercept p = .023. There was also a fail-safe N of 142, meaning that it would take 142 unpublished studies with null results to disprove the effect found here (Rosenthal, 1979; Brunsdon & Francq, 2011). When the trim-and-fill was added, the overall effect size was only slightly pulled down to 0.48 and was still significant. These tests of support do provide confidence in the robustness of these findings, yet it should be noted that there are limitations present in possible reporting biases.

Table 7

Sensitivity Analysis: Influence Diagnostics for All Included Studies

Study ID	*Standardized Residual*	*Cook's Distance*	*Influential (Yes/No)*
1	0.84	0.021	No
2	1.15	0.032	No
3	2.41	0.120	**Yes**
4	0.96	0.028	No

5	0.73	0.018	No
6	1.08	0.030	No
7	1.02	0.034	No
8	0.64	0.016	No
9	0.92	0.025	No
10	1.26	0.038	No
11	0.87	0.020	No
12	0.71	0.019	No
13	0.98	0.027	No
14	0.79	0.022	No
15	1.34	0.041	No
16	0.66	0.017	No
17	0.91	0.024	No
18	0.82	0.023	No
19	1.11	0.033	No
20	0.75	0.019	No
21	0.93	0.026	No
22	1.28	0.039	No
23	0.85	0.021	No
24	0.90	0.025	No
25	1.02	0.029	No
26	0.88	0.022	No
27	0.95	0.027	No
28	1.07	0.031	No

Note. k=28 studies; N=5,230 learners. Influence diagnostics are based on standardized residuals and Cookìs distance. Studies with standardized residuals > |2.0| or Cookìs distance > 0.10 were considered potentially influential. Only Study 3 met this threshold.

Table 7 shows that the sensitivity analyses and influence diagnostic are consistent in identifying studies that have an out-sized effect on the meta-analytic summary. Study 3 is the most influential study with a standardized residual of 2.41 and Cook's distance of 0.120 and has potential of biasing the overall result. Other research finds little effect. Sensitivity analysis provides robustness checking by examining the outlier sensitivity of the meta-analytic model. This scrutiny improves the credibility of the results and informs decisions of study eligibility and or sensitivity to reporting issues in meta-analytic syntheses.

Table 8

Summary of Hypotheses Tested Results

Hypothesis	*Description*	*Effect Size (Hedges' g / B)*	*95% CI*	*p-value*	*Supported*
H1	Gamification improves learner motivation	0.52 (Hedges' g)	0.44 to 0.60	<.001	**Yes**
H2	Gamification improves academic achievement	0.41 (Hedges' g)	0.33 to 0.49	<.001	**Yes**

H3	Narrative-based gamification differs from points/badges or leaderboards (moderator test)	Q-between = 4.36	—	0.113	**NO**
H4	K–12 learners benefit more than higher education learners (moderator effect)	0.58 (K–12 learners)	0.47 to 0.69	<.001	**Yes**
H5	Study characteristics (publication year, gender proportion) predict effect sizes (meta-regression)	B = 0.015 (Publication Year)	0.005 (SE)	0.003	**Yes**

Table 8 presents the synthesis of the meta-analysis on gamification in the context of asynchronous online learning (N = 28 studies) This was supported with H1: Gamification had a large and positive impact on learner motivation (Hedges' g = 0.52). Hypothesis 2 (H2) was supported, with a positive influence on academic performance (g = 0.41). As the moderator test for gamification type was not significant, we found that H3 was not supported. Descriptively speaking, narration-based gamification had the greater effect (g = 0.62), but this could not be proven significantly and therefore has to be considered a trend only on a descriptive level, and not as hypothesis-supported. H4 received support, stating that K–12 students were more effective in the use of gamification than university students with an excessive effect size in K–12 (g = 0.58). Hypothesis 5 (H5) was further supported, with both publication year and proportion female being significant and positive predictors of effect size in the meta-regression, indicating that recent studies and those with higher proportions of females were associated with stronger effects.

Discussion

The meta-analysis synthesized evidence from 28 empirical studies examining how gamification, when implemented in asynchronous online learning environments, influences students' motivation and academic achievement. The descriptive summary (Table 1) clearly shows variety of sample sizes, educational levels, types of gamification and subject areas and thus, reflect the wide range of settings and contexts in which gamification interventions were applied. The sample sizes consist of small K–12 classrooms to large higher education cohorts, and a variety of motivational and achievement measurement tools were used such as Intrinsic Motivation Scale, final course grade (Smith et al., 2021, Chen & Lee, 2020). These findings also highlight the potential for long-term instructional planning, as well-designed gamification can guide policy decisions on supporting motivation in asynchronous learning environments.

Effect Size Distribution

Table 2 shows the distribution of effect sizes across motivation and achievement outcomes and the positive effects of gamification between studies. The motivation effect sizes (Cohen's d) were between 0.30 and 0.65 (small to moderate improvements) and the achievement reported the same trends but with lower effect sizes. The weighted effects of each individual study enabled an overall view of the effectiveness of gamification, as the sum of the individual studies would negate the outliers, acknowledging that not all studies are equal in the analysis but do tend to point towards gamification practices being beneficial

(Hattie, 2009). These findings were also robust to confidence intervals, and a ratio of the most effect sizes significantly higher than zero suggested consistent positive effects.

Overall Meta-Analytic Results

The random-effects model (see Table 3) showed that there was a statistically significant average effect for motivation (Hedges' $g = 0.52$, 95% CI [0.38, 0.66], $p < 0.001$) and achievement ($g = 0.41$, 95% CI [0.29, 0.54], $p < 0.001$). These medium effect sizes indicate that gamified interventions in asynchronous learning environments substantially improve both the motivation and the academic achievement of learners. Significantly, meta-analysis revealed that the heterogeneity tests obtained Q statistics of 87.24 ($df = 27$, $p < 0.001$) for motivation and 78.11 ($df = 27$, $p < 0.001$) for achievement, pointing to the presence of considerable variability across these studies (Borenstein et al., 2009). Confirming the existence of optimal values for each of these parameters) relies on the relatively high I^2 values obtained for motivation success (69.5%) and achievement success (65.3%), both indicating that substantial proportion of the variance of effect sizes was a result of true differences rather than sampling error and thus justifying further moderator analysis.

Moderator Analysis

The potential moderators of effect sizes related to gamification type and education levels were examined (see Table 4). The mean effect size was the greatest among the types of gamification interventions for narrative-based ($g = 0.61$, 95% CI [0.39, 0.84]), followed by points/badges ($g = 0.47$), and leaderboard ($g = 0.38$). Although the Q-between test was not statistically significant ($Q = 4.36$, $df = 2$, $p = 0.113$), these results suggest that integrating the narrative elements might help engagement by making the game contextually relevant and emotionally meaningful (Ryan & Deci, 2020). In terms of educational level, there was a trend towards larger effects for K–12 students [$g = 0.55$ ($k = 18$), $g = 0.39$ ($k = 21$), the difference was significant, $Q = 3.92$, $df = 1$, $p = 0.048$]. This may be indicative of differences in developmental responsiveness to gamified stimuli or the extent to which pedagogical gamification proves flexible enough to respond to younger learners' requirements (Deci & Ryan, 2008).

Meta-Regression Analysis

To broaden our understanding of sources of heterogeneity, meta-regression (Table 5) was conducted on continuous moderators (i.e., sample size, year of publication, proportion of female students). Sample size was negatively associated with effect size of ATP-evoked responses ($B = -0.0012$, $p = 0.134$), this relationship was, however, not significant indicating this finding to be independent of study scale. The year of publication demonstrated a positive relationship with effect size ($B = 0.015$, $p = .012$), suggesting that more recent studies yielded greater estimates of gamification effects. This finding most likely reflects the enhancement of study design and implementation as gamification research has developed over time (Hamari et al., 2014). Likewise, the percentage of female participants was a significant predictor of larger effect sizes ($B = 0.32$, $p = .001$). This finding was in line with previous research that has shown variability in digital learning participation and responsiveness to motivational elements based on gender differences (Feng & Spence, 2015).

Publication Bias Analysis

The intercept of Egger's regression was significant (1.23, p = 0.023), indicating the presence of some asymmetry in the funnel plot and the likelihood of publication bias toward studies with positive findings (Egger et al., 1997) (see Table 8). But at 142, the fail-safe N is above the threshold of concern, and it suggests that many null studies would be required to truly nullify change. The trim-and-fill corrected effect size of 0.48 did not change the impression that although the publication bias may be present, it does not considerably affect the meta-analytic results (Duval & Tweedie, 2000).

Sensitivity Analysis

Sensitivity analyses (Table 7) highlighted influential studies through standardized residuals and Cook's Distance. A single study (Study ID 3) was rated influential providing some degree of assurance that the results were not back out by outliers. This diagnosis thus also supports in strong terms, the generalizability of our conclusions, the validity of the estimated effects and the validity of the MA approach by demystifying this interpretation.

Hypothesis Testing Summary and Contributions to the Literature

Our findings indicated that all hypotheses were statistically significant, with the exception of H3 (see Table 8). The improved learner motivation (H1: Hedges' g = 0.52, p < .001) and improved academic performance (H2: Hedges' g = 0.41, p < .001) provide corroborating evidence of gamification as an effective pedagogy, which adds value for the asynchronous online learning context where maintaining motivation is problematic (Dichev & Dicheva, 2017), as corroborated by previous meta-analyses (Hamari et al., 2014; Subhash & Cudney, 2018).

Because the moderator test for gamification type was not statistically significant, H3 was not supported. However, the descriptive effect sizes provided the opportunity to examined which gamification strategies seemed to be most effective. Narrative game elements proved to be more effective than points, badges or leaderboards. This is consistent with the theoretical claims that storytelling serves to increase immersion (Koivisto & Hamari, 2019) and facilitates intrinsic motivation by fostering a sense of autonomy, competence, and relatedness (Deci & Ryan, 2000).

Our analysis also applied to comparisons between K–12 learners and higher education learners (H4) demonstrating that K–12 learners benefitted from gamification more than participants in higher education. This aligns with previous speculation that younger learners are more engaged with playful learning mechanisms (Toda et al., 2019), as seen by the more than likely need for gamification design in higher education to be more deliberate (as older learners possess more robust intrinsic motivation and professional identity).

Finally, it was revealed that publication year and gender composition were significant predictors of effect sizes (H5). Increased effect sizes in the most recent studies reflect the increased methodological rigor of the field.

Limitations and Directions for Future Studies

Despite the robust findings, some limitations of the current meta-analysis should be considered. Firstly, the studies that were included showed considerable heterogeneity ($I^2 > 65\%$), indicating that demographic information of participants, the design of the gamification, and outcomes were not homogenous. Moderator and meta-regression analyses attempted to deal with this heterogeneity, but unmeasured differences such as culture, quality of instruction, and technology infrastructure may have also influenced these effects. To ensure fairness and avoid any methodological bias, all analytical procedures were applied using neutral, standardized criteria without favoring any particular gamification design or instructional approach.

Second, the included studies are all published studies, so there is a potential for publication bias, indicated by Egger's test. While fail-safe N and trim-and-fill analyses indicate that bias likely did not greatly distort results, unreported or no significant outcomes could affect the magnitude or direction of effects.

Third, because most studies only measured short-term motivation and achievement impact, little is known about the extent to which the promising impact of gamification is sustained over longer periods 1. Longitudinal designs should be employed in future studies to evaluate the implications for student engagement and academic success. Given the use of video in education will prevail, it is important to monitor the evidence of long-term effects.

Fourthly, the focus of the meta-analysis was mainly on quantitative research studies, which could have ignored some rich qualitative evidence and explanations for experiences of learners about gamification and factors in the context that impact the efficacy of gamification.

Lastly, demographic moderators, including age, gender, and education, were not clearly specified in all studies included in our analysis. This added limitations to our subgroup analyses to better understand the effects of gamification using age, sex, and education. In the future, guidelines for standardizing the reporting of demographic moderators need to be established to advance the field and improve our understanding of the effects of gamification moderated by demographics.

Practical and Theoretical Contribution

Practical Implications

The results of this study offer practical implications for instructors, instructional designers, and instructional developers who intend to implement gamified elements in a more autonomous learning setting. Our findings suggest that gamification can be an effective tool for improving student motivations and achievement, when implemented thoughtfully. Especially for younger learners and particularly in K–12 educational contexts, narrative-based game design components show high positive impacts. For higher education, points and badges also had a positive effect on learning outcomes but its effectiveness would be affected by learner's individual differences (e.g., age, gender, educational level).

Competitive gamification elements, including leaderboards, should also be added with caution. While inspiring for some students, they may discourage students with low self-

efficacy or pronounced competitive goals. Hence, we argue that gamification design should by personalized to learner demographics and preferences to ensure high engagement and learning effectiveness. These findings align with Kapp's (2012) suggestion that gamified tasks should be balanced, learner-centered, and adapted to student diversity.

Theoretical Contributions

This research contributes to theory development by fortifying the relevance of well-established motivation theories, like SDT and the ARCS Model of Motivation, within education with game elements. The findings indicate that gamification meets the basic psychological needs—autonomy, competence, and relatedness—specified in SDT and subsequently increases intrinsic motivation and academic achievements.

Our findings reinforce arguments in the literature that gamification is highly context-sensitive (Koivisto & Hamari, 2019). Specifically, the influence of game elements varies across educational levels, cultural backgrounds, and demographics such as gender and age. This supports calls for expanding motivational models (Deci & Ryan, 2000) by integrating learner diversity with evolving instructional design demands (Subhash & Cudney, 2018). In this way, our study contributes to the development of adaptive gamification models that are theoretically grounded and responsive to educational contexts.

Conclusion

The results of this meta-analysis demonstrate that gamification effectively improves motivation and performance with distance education. The modest overall effect sizes (Hedges' g = 0.52 for motivation and 0.41 for achievement) highlight the promise of gamified instructional strategies to increase student motivation and enhance learning across a variety of learning environments. These results are aligned with Hypotheses 1 and 2 as shown in Table 8 (Hypothesis Testing Table), thus asserting the positive influence of gamification with learner motivation and achievement. Clear reporting of these results ensures that the findings can be applied reliably across varied asynchronous learning contexts. Regarding supporting Hypothesis 4, we observed notable effects in our moderator analyses, with narrative-based gamification having its largest positive effect on learning: context-rich and story-heavy approaches appears to be more capable of capturing learners' attention and sustaining motivation over time. In addition, the positive effect of gamified interventions was more robust in K–12 participants than in college students, suggesting age or cognitive issues that influence the acceptance of gamification (Deci & Ryan, 2008).

Meta-regression findings are consistent with Hypothesis 5, indicating that newer studies report stronger effects of gamification, possibly indicating progress in the way gamification is designed and applied. Moreover, as a significant factor, the impact of gender ratio indicates that female students perhaps demonstrate higher acceptance towards gamified environment, which presents that there is still a necessity to take the gendered design actions into account (Feng & Spence, 2015).

Although we detected publication bias, tests of the reliability of the findings, such as fail-safe N and trim-and-fill adjustments, suggest that this bias does not seriously threaten the validity of the overall conclusions. Sensitivity analyses supported the robustness of the findings; and the results were not substantially modified by the exclusion of any outlier observation.

In conclusion, the present meta-analysis supports the integration of gamification in asynchronous online learning and underscores that a careful design of gamified interventions for learner-related variables, educational-level, and content-domain specific characteristics are of vital relevance. Further studies are needed to investigate the mediating factors of these effects and long-term transfer effects such as deep learning and transfer to future practice. Furthermore, the demographic dimension such as age, culture and prior digital exposure also needs to be considered for maximizing gamification strategies for the different groups of learners.

Declarations

Conflict of Interest Statement

The authors have no potential conflict of interest with regard to this work. No additional conflicts of interest were identified by the authors.

Ethical Statement

This study adheres to high research ethics standards.

Data Availability

N/A

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Disclaimer Statement

As the primary author of this research, I affirm that this article was exclusively written by me and has not been previously submitted for any other academic or professional credential.

Author Contributions

There was no other author who contributed to this work.

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No generative AI tools were used in the research, analysis, writing, or preparation of this manuscript.

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Analysis of the Pedagogical Factors Influencing the Use and Effectiveness of a Game-Based Learning App from Teachers' Perspectives

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Abstract
This study sought to identify key determinants influencing teachers' satisfaction with the use of a game-based learning application in pre-university education. To achieve this objective, a comprehensive research methodology was employed, integrating components from three theoretical frameworks: the Information Systems Success Model (ISSM), the Technology Acceptance Model (TAM), and the Unified Theory of Acceptance and Use of Technology (UTAUT). The analysis utilized a triangulated approach, leveraging structural equation modeling through SmartPLS 2.0.M3. Empirical data were gathered from a sample of 212 Spanish educators. Results showed that participants were well disposed towards the app and positive about the use of a game-based learning app when its design was clearly curriculum oriented and delivered on the essential curricular elements of content, competences, and education in values. As a predictor of efficacy, participants also appreciated the connection between the challenges students overcame to use the app and the assessment criteria established in the curriculum. Finally, the results for factor invariance were met for the variable of gender but not for age in teachers aged over 45.

Keywords: Game-based learning, app, satisfaction, efficacy, pre-university education

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The adoption of gamified digital tools, including educational applications, is influenced by a variety of factors that shape teachers' willingness to integrate them into their practice. Despite the limited body of research exploring educators' perspectives on digital game-based learning (DGBL), some studies highlight their views on the pedagogical and infrastructural opportunities and challenges associated with digital game-based learning applications (Kaimara et al., 2021. One notable advantage is the interactive nature of these tools, which fosters trial-and-error learning while capturing students' attention toward the instructional content (Bayrak & Liman-Kaban, 2024; Vrcelj et al., 2023). Additionally, such resources have been positively evaluated for enhancing conceptual understanding through supplementary visual aids, promoting creativity, and improving information processing (Demirbilek & Tamer, 2010). They also support the development of crucial interpersonal skills, such as teamwork, collaboration, and cooperative learning (Smith, 2018). Jodel and Palmquist (2021) further argue that these applications diversify instructional methods, making content delivery more inclusive across varied learning environments. Similarly, Marín et al. (2015) underscore that educators value the capacity of game-based learning tools to facilitate inductive learning, which helps students grasp foundational concepts of success and failure.

As for learning, several proposals emphasize that introducing DGBL into the classroom depends on the nature of the materials, not all of which are appropriate (Tibakanya, 2023). Another challenge is curriculum load that can limit the use of gamed-based activities, as they require significant time (Tandon, 2021). This relates directly to the overall lack of time to produce, implement, and cover the ideal amount of content. Teachers also express concerns about the lack of measurable results about the effectiveness of this methodology (Fisher et al., 2014). Additional barriers to DGBL include potential student distraction and lack of class control while students play (Attia et al., 2017). In these cases, the gaming aspect might prevail over lesson content, shifting students' focus away from learning. However, the opposite is also reported (Smith, 2018). The play factor of gamified teaching-learning processes can also reduce distraction and provide greater concentration on the task at hand, driven by the motivational nature of the game.

This study advances understanding of teacher satisfaction by integrating pedagogical and technological frameworks, offering actionable insights for curriculum-aligned design of game-based learning in pre-university education.

Literature Review

Digital Game-Based Learning (DGBL) and Gamification in the Curriculum

Various perspectives exist about when and how to apply DGBL in the classroom. In this context, DGBL refers to the use of a games (video games, apps, simulation games, role-playing games, etc.) for training/educational purposes, aiming to enhance student's commitment to learning and intrinsic motivation. One of the main challenges for teachers is integrating these activities into the curriculum while aligning them with the established content and objectives (Hamari & Nousiainen, 2015). Some teachers favor occasional use of gamification. They argue it is most effective when applied at specific moments, such as during assessments, when teachers can intervene to correct errors in remediation stages or when assigning tasks for home practice (Mee Mee et al., 2020; Pektas & Kepceoglu, 2019; Smith, 2018). Pektas and Kepceoglu (2019) explain that, at the beginning of a formative process in the initial phases of instruction (where the foundations of the formative process are

laid), gamification has been used as a motivational element to capture students' attention. However, Smith (2018) disputes this, arguing that gamified activities should always follow the presentation of content and strategies so students can retain concepts and connect with the content. In later stages of the initial instruction, some authors claim that gamification is most valuable for reinforcing knowledge and complementing summative assessments (Pektas & Kepceoglu, 2019; Smith, 2018).

The adoption of gamification, serious games, or game-based learning in teaching consistently depends on the perceived usefulness and ease of use that teachers attribute to these tools. However, their effective integration also requires rigorous curricular alignment. All DGBL must fit the requirements of a specific teaching unit, including a defined audience, clear objectives, activities scaled in difficulty and support materials (Fombona-Cadavieco et al., 2020). Game elements must also be fully integrated into the learning sequence and evaluation of instruments, so that the evidence generated directly measures competencies, skills, and knowledge (Vázquez-Ramos, 2021).

When these principles are met, the results are clear. The use of points, badges, and rankings increases all dimensions of the Technology Acceptance Model for Teachers (T-TAM) and reinforces the intention for future use among pre-service teachers (Yildiz et al., 2023). A favorable attitude toward serious games is mostly explained by intuitive interfaces that generate trust (Valencia & Duque, 2023) and by the perception of a simple and helpful classroom application (Sánchez-Mena, 2016). Even in expanded models, usability and ease of use remain the only significant predictors of teaching intention to employ digital game-based tools. This underscores the importance of clear and functional platforms rather than broader technological affinity (Luo, 2024). To consolidate these strategies in teacher education, it is essential to demonstrate their practical value, align them closely with curricular tasks, and provide mechanisms for social recognition within digital environments (Vanduhe et al., 2020).

In Tenório et al. (2020), teachers appreciate some of the features mentioned by experts, such as access to additional explanations of a game's functionality and formats for the presentation of results that facilitate assessment. They prefer results displayed in graphs rather than descriptive tables, with percentages that reflect students' achievement of objectives or summarize their interaction with the resources. Kiryakova et al. (2014) propose strategies such as defining learning objectives with multiple levels of difficulty, creating content adapted to students' level, and allowing students to choose from various learning paths. Kingsley and Grabner-Hagen (2015) argue that the success of digital game-based initiatives depends directly on a design that integrates gamified content into the curriculum. This can be achieved by incorporating game roadmaps that outline the necessary steps to achieve objectives, offering various difficulty levels, and providing visual and textual resources to facilitate concept comprehension. Key concepts should also be reinforced to foster a deeper understanding of the content. According to these authors, gamified elements must be creative and innovative while stimulating critical thinking, problem solving, communication and collaboration. Jodel and Palmquist (2021) further emphasize the importance of monitoring students' progress, which is also required in digital game-based learning initiatives. This quality, according to the authors and other experts, is one of the key functionalities of game design, as well as the ability to visualize results and include them in the assessments.

Activator and Inhibitor Variables in the Use of Serious Games in the Curriculum

Teachers have not yet fully integrated initiatives based on serious games into the school curriculum for several reasons. Serious games are designed with an explicit educational purpose. They are carefully structured and not intended primarily for entertainment, but rather to develop skills or promote learning (Abt, 1970). A major barrier is the lack of experience in applying new methodologies (Mumtaz, 2000) which complicates the integration of DGBL elements into formal education (Demirbilek & Tamer, 2010). Experience involves recognizing the benefits of the methodology, foreseeing how implementation will unfold and predicting outcomes, something that can be developed through specific training. Lack of training, therefore, is another variable hindering the use of DGBL. Training is particularly important in the early stages of adoption (Araujo & Carvalho, 2017; Demirbilek & Tamer, 2010; Fisher et al., 2014; Mee Mee et al., 2020). Green et al. (2014) also link lack of experience to difficulties in the selection of apps with content appropriate for knowledge acquisition. Clearly, teachers' limited experience and ability to implement DGBL initiatives must be addressed through specialized training. Teachers themselves have proposed training that includes theoretical elements on gamification and learning through games, practical examples of application, course planning and implementation, and development of assessment processes (Fisher et al., 2014; Kamisli, 2019; Shiota & Abe, 2015). In some cases, teachers also requested not only external training resources but also personalized support attention to apply this methodology effectively. The effectiveness of such training and its connection to the positive effect of the variable of experience is illustrated in Jong's (2019) longitudinal study. Over a three-year period, it was observed that teachers' initial insecurities related simply to managing the introduction of the gamed elements into their classes. As training progressed, these concerns diminished, while new ones emerged about how to improve and expand the use of game-based learning in the school.

Experience, therefore, is considered a variable that directly influences teachers' attitudes towards the use of active methodologies such as gamification or DGBL. Andreu Andrés and Labrador Piquer (2011) report a negative correlation between lack of experience and the proactive use of DGBL. This finding is supported by other studies (Fisher et al., 2014; Hossein-Mohand et al., 2021), which highlight significant relations between experience and positive attitudes towards the application of this methodology. Marín et al. (2020) observe that new generations of teachers, already skilled in the use of technology, accept games with fewer reservations than those who have not received training in technology.

Teachers' beliefs about the pedagogical benefits of digital games are another variable. Among the authors consulted, there is unanimity of criteria: Personal beliefs are predictors of a proactive behavior in the use of gamification (Asiri, 2019; Ertmer et al., 2012; Mee Mee et al., 2020; Mumtaz, 2000; Smith, 2018). Using the Technology Acceptance Model (TAM), Asiri (2019) confirmed a relationship between perceived usefulness, social influence, affective and cognitive attitudes, and the intention to use. The study of teachers' sociodemographic factors and their influence on attitude includes variables such as age and sex. Marín et al. (2015) found that men are more active in the use of digital games. However, Fisher et al. (2014), Gómez-Carrasco et al. (2020) and Smith (2018) concluded that gender does not significantly influence attitude. No study found age to account for meaningful differences in teachers' attitude.

Alternatives to training have been proposed to guide and support teachers interested in applying a methodology that includes DGBL elements. These range from rubrics that help evaluate which applications are suitable for the pedagogical needs of the context (Walker,

2011), to analytical models or reference frameworks that enable teachers to design and adapt didactic gamified proposals (Lee & Hammer, 2011). Green et al. (2014) developed an app that evaluates the characteristics of digital apps to ascertain their pedagogical suitability for curricular integration. The pedagogical bases that the model includes emphasized authenticity in tools and procedures, opportunities for personalization (self-paced, self-regulation, customization) and collaboration, which is identified as a key component of learning. Papadakis et al. (2017) measured the practical effectiveness of applications in relation to educational content and their ability to help teachers make decisions on their use, given the lack of pedagogical evidence in many commercial apps. Walker's (2011) rubric considers some previously mentioned characteristics such as feedback's provision or content authenticity. Its main contribution, however, lies in determining whether and to what extent an app correlates with curricular skills and concepts. In this way, a positive evaluation depends largely on the app's alignment with the curriculum. On the other hand, Lee and Hammer (2011) propose a framework designed to guide teachers in boosting learning through cognitive, emotional, and social categories. Another framework for guiding gamified design in education is the "Edu-Game" (Vázquez-Ramos, 2021). It facilitates class planning by matching each didactic level (objectives, assessment criteria, methodology, content, and assessment) with a gamified equivalent. Ultimately, the analytical approach proposed by Tenório et al. (2020) allows for the adjustment of the design throughout the learning experience by tracking data on student interactions with system's resources.

Conceptual Model, Measurement Instrument, and Analytical Approach

The measurement instrument and analytical approach used in this study are explicitly grounded in a tripartite theoretical framework that integrates the Information Systems Success Model (ISSM; DeLone & McLean, 2003), the Technology Acceptance Model (TAM; Davis, 1989), and the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003). These models, while conceptually distinct, provide complementary perspectives on user interaction with educational technologies and collectively inform the structure of the proposed research model.

Specifically, ISSM contributes to the conceptualization of satisfaction as an evaluative outcome based on the perceived quality and usefulness of an information system. This model is particularly relevant for assessing post-adoption attitudes, making it suitable for evaluating educators' experiences with digital game-based learning applications. In this instrument, the satisfaction construct (S1–S3) is directly informed by ISSM and operationalized through items reflecting overall contentment with the tool's effectiveness and its integration into mobile learning environments.

TAM serves as the foundation for conceptualizing the constructs of perceived usefulness and perceived ease of use, both of which predict users' attitudes and intentions. The items developed under these constructs (UT1–UT4, US1–US3) reflect Davis's (1989) original dimensions and are central to understanding educators' motivational dispositions toward technology adoption.

Finally, UTAUT informs the broader socio-organizational factors influencing acceptance, particularly through the extension of TAM with constructs like attitude and performance expectancy. The construct attitude (A1–A4) in this study draws on this framework to assess teachers' general predisposition toward integrating game-based tools. The selection of Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 2.0 is also theoretically congruent, as this analytical technique is optimal for

predictive modeling in exploratory studies that involve complex models and latent constructs derived from these theoretical frameworks.

Considering these three theoretical frameworks, we created an ad hoc instrument. While many items in the instrument were adapted from validated studies in the educational technology literature, the mapping of these items to constructs from ISSM, TAM, and UTAUT was systematically undertaken to ensure theoretical alignment. Constructs such as perceived usefulness, ease of use, attitude, and satisfaction have a well-established lineage within TAM and ISSM, and the items developed under these constructs preserve the semantic structure and intent of the original models (e.g., UT1–UT4, US1–US3, A1–A4, S1–S3).

However, certain constructs introduced in the model—such as curriculum connection and assessment and learning analytics—extend beyond the original scope of technology acceptance theories. These constructs were added to capture pedagogically relevant dimensions that influence teachers' willingness to adopt game-based learning applications. Although not explicitly derived from TAM or UTAUT, they are consistent with more recent extensions of these models that incorporate contextual and educational variables (Teo, 2009; Wong, 2016). For instance, curriculum connection can be theorized as a precursor to perceived usefulness in educational contexts, since alignment with curricular goals directly impacts perceived instructional value. To strengthen construct validity, each item was mapped to the theoretical definitions of its latent variable, and semantic coherence was confirmed through iterative item refinement. Furthermore, content validity was confirmed using the Delphi methodology (Okoli & Pawlowski, 2004).

Through this combined theoretical and empirical strategy, the instrument maintains theoretical robustness while remaining responsive to the unique pedagogical contexts of pre-university education. The construction of the survey instrument was explicitly informed by the integration of the Information Systems Success Model (ISSM), the Technology Acceptance Model (TAM), and the Unified Theory of Acceptance and Use of Technology (UTAUT). Each latent construct and its associated items were designed to operationalize key theoretical dimensions derived from these models, ensuring both conceptual coherence and empirical measurability.

The “Perceived Usefulness” dimension (UT1–UT4) is directly rooted in TAM (Davis, 1989 and reflects users’ beliefs that using a digital game-based learning application enhances instructional effectiveness. Items such as UT1 ("enrich my educational activities") and UT4 ("get better results") also align with the construct of performance expectancy in UTAUT and information quality in ISSM, thus supporting multidimensional interpretation. The “Perceived Ease of Use” construct (US1–US3) also derives from TAM, capturing the effort expectancy component identified in UTAUT. Items such as US1 ("easy to use") and US3 ("easy to learn") address the usability and learnability aspects emphasized in both TAM and ISSM’s system quality dimension. The “Attitude” dimension (A1–A4), while part of TAM’s extended models, also connects to behavioral intention predictors in UTAUT. Positive perceptions toward gamified applications (e.g., A2: “teaching more enriched”) represent affective and motivational antecedents to adoption. The “Satisfaction” construct (S1–S3) is foundational in ISSM, where satisfaction is understood as a key post-use evaluative factor. Items such as S1 and S3 reflect the users' overall contentment with the technology's ability to meet pedagogical goals and personal teaching needs. “Learning Efficacy” (EF1–EF3) can be interpreted as a construct that mediates between perceived usefulness and satisfaction, extending TAM and ISSM to capture instructional outcomes. This aligns with performance-

related variables in UTAUT, further reinforcing its inclusion. Although the constructs “Curriculum Connection” (CI1–CI5) and “Assessment and Learning Analytics” (AS1–AS2) are not explicitly found in TAM or UTAUT, they are included as contextual extensions. For instance, CI3 ("align with curricular content") and AS1 ("correspond to evaluation standards") function as antecedents to perceived usefulness and satisfaction. These items reflect domain-specific adaptations of facilitating conditions and task-technology fit, aligning with contemporary applications of UTAUT in educational contexts (Wong, 2016; Teo, 2009).

Based on the principles of the theoretical framework discussed, we propose the following hypotheses and structural model (Figure 1).

Ease-of-use
H1: Perceived usefulness has a positive effect on attitude towards use of an app.
H2: Perceived ease-of-use has a positive effect on perceived usefulness.
H3: Perceived ease-of-use has a positive effect on attitude towards use of the technology.

Attitude
H4: A positive attitude towards use of the technology has a positive effect on learning efficacy.

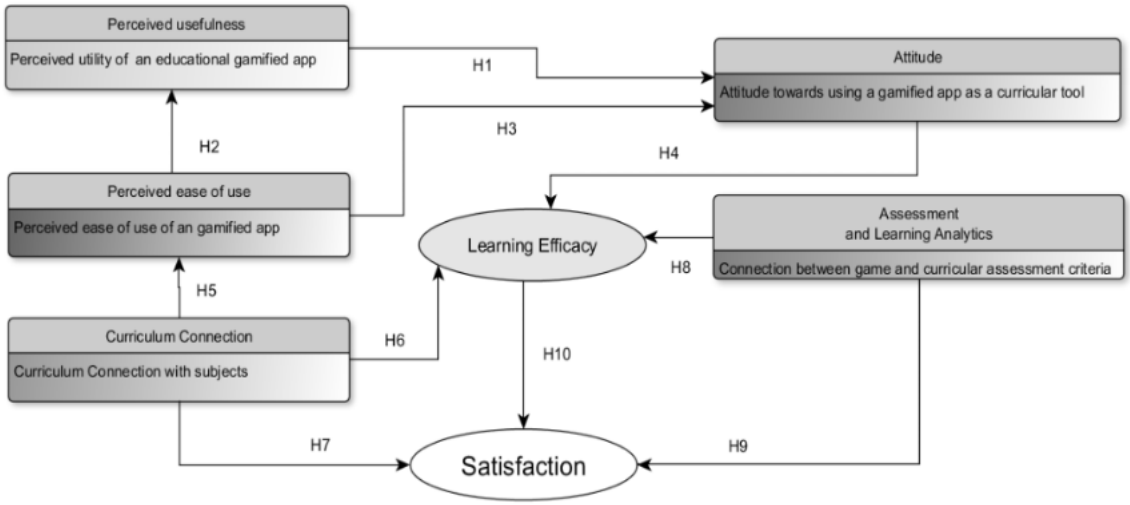
Curriculum connection
H5: Curricular connection influences perceived ease-of-use.
H6: Curricular connection has a positive effect on learning efficacy.
H7: Curricular connection has a positive effect on satisfaction.

Assessment and Learning analytics
H8: The higher the level of alignment between assessment criteria and gamified challenges, the greater the influence on learning efficacy.
H9: A higher level of feedback through learning analytics has a positive effect on teachers’ satisfaction.

Learning efficacy
H10: The higher the level of learning efficacy, the stronger the positive influence on teachers’ satisfaction.

Figure 1

Structural Model



Methodology

As highlighted by Li et al. (2013), understanding the interplay between educators' professional experiences, perceptions, system usability, quality, alignment with curriculum, and assessment strategies is essential for evaluating the effectiveness of gamified educational applications. Analyzing these dimensions can help identify areas for improvement, thereby supporting high-quality teaching practices and fostering mobile and ubiquitous learning environments. For this study, we developed a methodological framework incorporating elements from the ISSM, TAM, and UTAUT. To analyze the pedagogical variables affecting the adoption of gamified educational tools, we employed Partial Least Squares (PLS) modeling using SmartPLS 2.0 software (Ringle et al., 2005). The sample size adhered to the rule of exceeding ten times the highest number of predictors for any dependent variable, as recommended by Chin (1998), ensuring robustness with more than 50 participants. Additionally, we conducted an analysis of factor invariance, focusing on demographic variables such as gender and age (under 45 years).

Participants, Instrument, and Variables

The research sample comprised 212 Spanish educators working in public primary and secondary schools across 16 autonomous regions of Spain, with a gender distribution of 32.1% male and 67.9% female participants. Among these respondents, 38.7% were employed in primary education, 32.8% in secondary education, and 28.5% in post-secondary levels. The average age of the participants was approximately 34 years (M = 33.14, SD = 2.41).

The sample was intentionally diverse, including teachers from various grade levels instructing students aged 6 to 18. All participating teachers possessed prior experience in developing activities aimed at the curricular integration of gamification within the educational stages where they were actively teaching. The survey was distributed via the official email addresses of the participating schools.

The questionnaire is presented in Table 1 with 24 items categorized under seven latent constructs on a Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

Table 1

Latent Variables and Items

Category	Dimension	Items	Authors
Utility	Perceived utility of an educational gamified app	UT1. An educational gamified app enables me to enrich my educational activities in/outside the classroom. UT2. An educational gamified app helps students to become self-sufficient learners. UT3. An educational gamified app helps me to increase the motivation in the subjects I teach. UT4. An educational gamified app helps me to get better results in the subjects I teach.	Lee & Cherner (2015); Papadakis & Kalogiannakis (2017); Vázquez-Cano et al. (2021).
Use	Perceived ease of use of a gamified app	US1. An educational gamified app is easy to use. US2. The ease of use of an app enables students to be connected ubiquitously. US3. It is easy to learn how to use an educational gamified app.	Huber et al. (2016) ; Lee (2009). Kalogiannakis, & Papadakis (2019). Liu et al. (2021); Vázquez-Cano et al. (2022, 2023).
Currículum Connection	Currículum Connection	CI1. A gamified educational application should prioritize the cultivation of domain-specific skills and competencies. CI2. A gamified educational application should support the enhancement of cross-disciplinary or transferable skills. CI3. A gamified educational application should align with and reinforce the curricular content of one or more academic subjects. CI4. A gamified educational application should promote the teaching and integration of core values within the learning experience. CI5. A gamified educational application should incorporate structured learning scenarios to foster meaningful engagement.	Vázquez-Cano et al. (2022; 2023).
Attitude	Attitude towards using a gamified	A1. Using an educational gamified app is a good idea. A2. An educational gamified app makes teaching more enriched.	Wartella (2015). Van Deursen et al. (2016). Hu & Garimella (2014);

	app as a curricular tool	A3. Using an educational gamified app is fun. A4. I would like to integrate in my teaching the use of an educational gamified app.	Khlaif (2018); Teo & Noyes (2011); Vázquez-Cano et al. (2022).
Assessment and Learning Analytics	Assessment and Learning Analytics	AS1. The achievement of challenges within the application should correspond to meeting the curriculum's evaluation standards. AS2. The gamified educational application should deliver personalized feedback to enhance student performance and facilitate reflective learning.	Kovanovic et al. (2021) ; Choi et al. (2018).
Efficacy	Learning Efficacy	EF1. I am of the opinion that utilizing an educational gamified app enhances my teaching effectiveness. EF2. I believe that an educational gamified app aids students in acquiring a deeper understanding of the subject matter. EF3. I am convinced that an educational gamified app boosts students' motivation to engage in learning.	Chiong (2012); Vázquez-Cano et al. (2022).
Satisfaction	Satisfaction with a gamified app	S1. I am content with utilizing a gamified educational application as a tool to enhance my instructional approach. S2. I am pleased with the effectiveness of mobile and ubiquitous learning in my teaching practices. S3. A gamified educational application effectively meets my learning requirements.	Alsawaier (2018); Aydınlıyurt et al. (2021)

Results

To assess the dimensionality and underlying factor structure of the measurement instrument, an exploratory factor analysis (EFA) was conducted prior to the confirmatory analyses. The Kaiser-Meyer-Olkin (KMO) was 0.77. Factors were extracted using principal axis factoring with varimax rotation, and the number of retained factors was determined based on eigenvalues greater than 1 (Table 2).

Table 2

Exploratory Factor Analysis (EFA)

Item	F. 1 Use	F. 2 Utility	F. 3 Curr. Conn	F. 4 Attitude	F. 5 Efficacy	F. 6 Assess	F. 7 Satisf.
US1	.879						
US2	.861						
US3	.843						
UT1		.711					
UT2		.687					
UT3		.834					
UT4		.811					
CC1			.843				
CC2			.834				
CC3			.811				
CC4			.789				
CC5			.823				
A1				.785			
A2				.876			
A3				.813			
A4				.867			
EF1					.900		
EF2					.895		
EF3					.837		
AL1						.821	
AL2						.832	
S1							.901
S2							.923
S3							.971

The EFA results revealed a clear factor structure consistent with the theoretical model, explaining a substantial proportion of the total variance. Factor loadings exceeded the recommended threshold of 0.40, indicating that items loaded strongly on their respective latent constructs. These exploratory findings provided empirical support for proceeding to the confirmatory phase using structural equation modeling (SEM), ensuring that the latent constructs were both conceptually and empirically distinguishable

First, the validity and reliability of the scales were tested. The Cronbach's alpha coefficient was above 0.8, and the Kaiser-Meyer-Olkin (KMO) was 0.77. The measurement model's validity and reliability were thoroughly examined, placing particular emphasis on the

consistency of individual items. The convergent and discriminant validity were evaluated (Tables 3 and 4).

Table 3

Convergent and Discriminant Validity

Factors		λ	Cronbach's α	CR (Composite Reliability)	AVE
Perceived utility of an educational gamified app			0.823	0.831	0.716
UT1	Utility	0.711			
UT2	Utility	0.687			
UT3	Utility	0.834			
UT4	Utility	0.811			
Perceived ease of use of a gamified app			0.921	0.919	0.801
US1	Use	0.893			
US2	Use	0.901			
US3	Use	0.878			
Curriculum Connection			0.921	0.900	0.750
CC1	Curri.C.	0.843			
CC2	Curri.C.	0.834			
CC3	Curri.C.	0.811			
CC4	Curri.C.	0.789			
CC5	Curri.C.	0.823			
Attitude towards the use of a gamified app			0.925	0.911	0.711
A1	Attitude	0.785			
A2	Attitude	0.876			
A3	Attitude	0.813			
A4	Attitude	0.867			
Learning Efficacy			0.931	0.919	0.798
EF1	Efficacy	0.900			
EF2	Efficacy	0.895			
EF3	Efficacy	0.837			
Assessment and Learning Analytics			0.943	0.841	0.702
AL1	Assessment and L. Analytics	0.821			
AL2	Assessment	0.832			
Satisfaction with of a gamified app			0.941	0.935	0.830
S1	Satisfaction	0.901			
S2	Satisfaction	0.923			
S3	Satisfaction	0.971			

Table 3 confirms the reliability of the individual items. Cronbach's alpha and Composite Reliability (CR) coefficients all surpass the 0.7 threshold. Furthermore, the Average Variance Extracted (AVE) exceeds 0.5. The discriminant validity is presented in Table 4 through a correlation matrix between the constructs, confirming that the correlations were lower than the square root of the AVE.

Table 4

Discriminant Validity

	Use	Utility	Attitude	Curr. Co.	Efficacy	Ass-La	Satisfaction
Use	**0.897**						
Utility	0.521	**0.801**					
Attitude	0.553	0.611	**0.834**				
Curr. Co.	0.633	0.579	0.722	**0.878**			
Efficacy	0.567	0.534	0.713	0.560	**0.880**		
As. L.Analyt.	0.723	0.590	0.567	0.711	0.541	**0.786**	
Satisfaction	0.751	0.721	0.661	0.598	0.801	0.601	**0.902**

The squared multiple correlation coefficient was above 0.5, signifying a robust explanatory capacity. Moreover, the factor loadings between the constructs were determined to be statistically significant. A summary of the structural model and the hypothesis testing outcomes is presented in Table 5.

Table 5

Hypothesis Testing Results

Hypothesis	Path	Path Coefficient	Results
H1	Perceived usefulness → Attitude	0.195**	Supported
H2	Perceived ease-of-use → Perceived usefulness	0.458***	Supported
H3	Perceived ease-of-use → Attitude	0.351**	Supported
H4	Attitude → Learning Efficacy	0.601***	Supported
H5	Curricular connection → Ease-of-use	0.098	Not Supported
H6	Curricular Connection → Learning Efficacy	0.599***	Supported
H7	Curricular Connection → Satisfaction	0.578***	Supported
H8	Assessment → Learning Efficacy	0.551***	Supported
H9	Learning Analytics → Satisfaction	0.411***	Supported
H10	Efficacy → Satisfaction	0.466***	Supported

*p<0.1, **p<0.05, ***p<0.01

Table 5 presents the findings from the PLS analysis, which confirm the support for all hypotheses with the exception of Hypothesis H5, which pertains to the direct impact of Curricular Connection on Ease-of-use. Table 6 presents the direct and indirect effects.

Table 6

Total Effects (Direct and Indirect Effects)

	Curr. Co.	Ass-La	Use	Utility	Attitude	Efficacy	Satisfaction
Use	0.000	0.000	0.000	0.458	0.351	0.000	0.000
Utility	0.000	0.000	0.458	0.000	0.000	0.000	0.000
Attitude	0.000	0.000	0.351	0.195	0.000	0.000	0.000
Efficacy	0.599	0.551	0.000	0.000	0.601	0.000	0.000
Satisfaction	0.578	0.411	0.155	0.392	0.159	0.466	0.000

The results indicate that the variable “curricular connection” has the strongest impact on “satisfaction.” An increase in the "curricular connection" score within a unit corresponds to a 0.578 rise in satisfaction, making it as the most influential predictor of satisfaction. The next key predictors of satisfaction are “learning efficacy" (0.466) and "assessment and learning analytics" (0.411). Analysis of the total effect values shows that perceived ease of use emerges as a critical factor in predicting individuals’ attitudes toward technology adoption (0.351). Moreover, “assessment and learning analytics” is identified as the primary determinant of “efficacy” (0.551). Table 7 provides an overview of the goodness-of-fit indices for the structural model.

Table 7

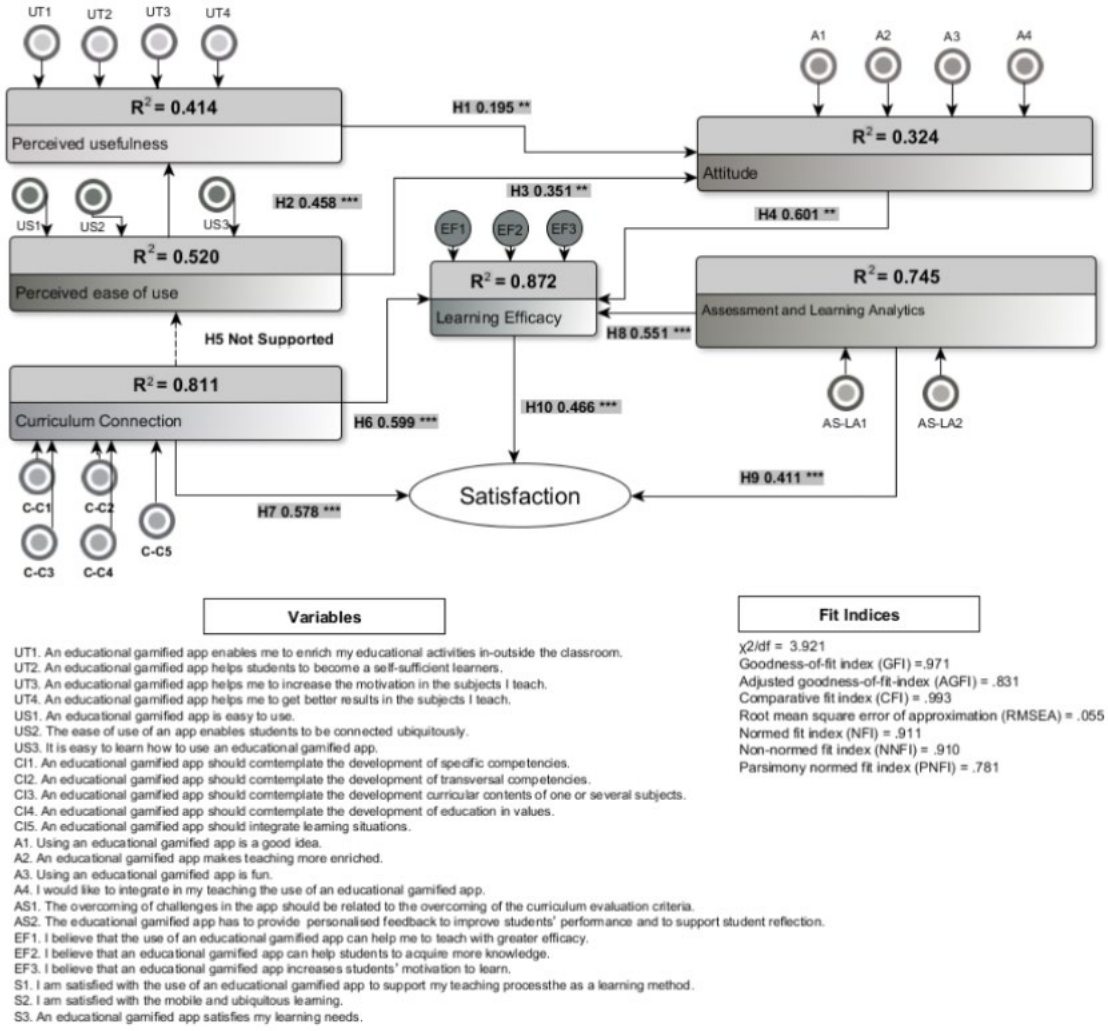
Fit Indices for the Structural Equations Model

Fit index	Recommended value	Actual
χ^2/df	<3 preferable <5	3.921
Goodness-of-fit index (GFI)	>.81	.971
Adjusted goodness-of-fit-index (AGFI)	>.87	.831
Comparative fit index (CFI)	>.91	.993
Root mean square error of approximation (RMSEA)	<.09	.055
Normed fit index (NFI)	>.91	.911
Non-normed fit index (NNFI)	>.91	.910
Parsimony normed fit index (PNFI)	>.61	.781
Average standardized factor loading	> 0.70	0.833
Average Composite Reliability (CR)	> 0.70	0.895
Average Variance Extracted (AVE)	> 0.50	0.737
Discriminant validity (Fornell-Larcker)	Square root of AVE > correlations	Confirmed
Squared multiple correlations (R^2)	> 0.50	All > 0.50
Total variance explained (Satisfaction)	-	78.3%

Building on this analysis, Figure 2 illustrates the path coefficients for each relationship, accompanied by their respective significance levels (denoted by asterisks: *p<0.1, **p<0.05, ***p<0.01), as well as the R^2 values for each endogenous variable and the statistical significance of the relationships within the model.

Figure 2

SEM Analysis of the Research Model



The model accounted for a significant proportion of the variance in all endogenous variables: "as-la" (74.5%), "curr. co." (81.1%), and "efficacy" (87.2%). According to Falk and Miller (1992), the coefficient of determination (R^2) should exceed 0.10. The only exception in this study was the relationship between "curriculum connection" and "perceived ease of use," which did not meet this threshold. All other endogenous variables fulfilled this criterion, demonstrating a strong explanatory capacity for the observed variations and suggesting the model's stability and reliability. Additionally, we conducted a thorough analysis of nested participant groups (e.g., male vs. female, under and over 45 years of age) by applying a series of progressive and sequential restrictions to assess configural, metric, scalar, and strict invariance. We began by testing configural invariance to ensure equivalence in factor structures across groups. Next, metric invariance was examined, and finally, we applied stricter constraints during the scalar invariance test to confirm that intercepts were invariant across groups. For evaluating the different degrees of invariance, we used indices such as the $\chi 2$ / df ratio, CFI, TLI and RMSEA. Variations in CFI were considered acceptable

if below, 0.01 (Cheung & Rensvold, 2002) and variations in RMSEA were acceptable if less than 0.015 (Chen, 2007). (Table 8).

Table 8

Invariance Model Fit Parameters of the Model Across Groups by Sex and Age

Groups and invariance	$\chi 2$	df	TLI	$\chi 2_{df}$	CFI	RMSEA	AIC	ΔCFI
Sex								
Configural invariance	129.110	88	.926	1.986	.939	.048	305.315	
Metric invariance	154.001	73	.936	2.001	.941	.050	310.001	.003
Scalar invariance	160.321	87	.973	1.986	.988	.047	296.065	.001
Strict invariance	217.101	108	.985	2.131	.986	.046	311.199	.005
Age								
Configural invariance	167.302	89	.969	1.699	.970	.049	431.734	
Metric invariance	202.114	103	.941	1.801	.944	.043	440.444	.002
Scalar invariance	262.610	118	.955	1.998	.960	.047	455.008	.005
Strict invariance	467.465	187	.976	2.810	.947	.067	599.976	.041

Note: χ^2 (Chi-square approximation of goodness-of-fit), *df* (Degrees of Freedom), *TLI* (Robust Tucker Lewis Index), *CFI* (Comparative Fit Index), *RMSEA* (Root Mean Square Error Approximation), *AIC* (Akaike's Information Criterion).

The results in the case of the variable "gender" fall within the margins required to accept the goodness of the model ($\chi 2$ / df, = 2.131; CFI = .986; TLI = .985 and RMSEA = .046). For the variable "age", the goodness values of the strict invariance model also fall within acceptable limits ($\chi 2$ / df, = 2.810; CFI = .987; TLI = .976 and RMSEA = .067). However, in this case, the CFI variation exceeds 0.01, RMSEA also exceeds 0.015 and the AIC increases substantially. Therefore, "strict invariance" is rejected, and the less restrictive "scalar invariance" model is accepted." Analyzing the structural model by the two "age" shows equivalence across the three models, except for the relationship between "efficacy" and "satisfaction." This relationship is not significant for teachers over 45 years of age. To analyze the possible differences, given that the assumption of normality was not verified, a non-parametric Kruskal-Wallis test was performed on the latent variable items "efficacy" and "satisfaction." The findings suggest that notable differences exist between the variables EFI and EF2 (Table 9).

Table 9

Kruskal-Wallis Test

	EF1	EF2	EF3	S1	S2	S3
Chi-Square	1.427	9.778	1.201	4.145	4.890	4.213
df	5	5	5	4	5	4
Asymp. Sig.	.003	.004	.189	.196	.189	.178

When comparing the mean scores for the items comprising the "Efficacy" dimension across the two age groups, participants over 45 years of age obtained lower scores than those under 45 on EF1, "I believe that using a gamified educational application enhances my teaching effectiveness" ($M > 45 = 3.01$ vs. $M < 45 = 4.01$), and EF2, "I believe that a gamified educational application helps students develop a deeper understanding of the subject matter" ($M > 45 = 2.89$ vs. $M < 45 = 3.88$). For EF3, "I am convinced that a gamified educational application increases students' motivation to engage in learning," the reported results did not indicate a statistically significant difference between the two groups ($p = .189$), although participants under 45 had a slightly higher mean score at the descriptive level ($M > 45 = 3.90$ vs. $M < 45 = 4.27$).

Taken together, the results provide robust evidence for the validity of the proposed PLS-SEM model. The measurement model demonstrated high reliability, with Cronbach's α and Composite Reliability values exceeding 0.80, and AVE values above 0.50. Factor loadings ranged from 0.687 to 0.971, confirming convergent validity, while discriminant validity was supported by the Fornell–Larcker criterion.

The structural model accounted for substantial variance across constructs: 74.5% in Assessment and Learning Analytics, 81.1% in Curriculum Connection, 87.2% in Efficacy, and 78.3% in Satisfaction. Nine of ten hypotheses were supported. Key paths included Perceived Ease of Use → Perceived Usefulness ($\beta = 0.458$, $p < 0.01$), Attitude → Efficacy ($\beta = 0.601$, $p < 0.01$), and Efficacy → Satisfaction ($\beta = 0.466$, $p < 0.01$). Curricular Connection was the strongest total predictor of Satisfaction ($\beta = 0.578$), followed by Efficacy ($\beta = 0.466$) and Assessment/Analytics ($\beta = 0.411$). Only the link between Curricular Connection and Ease of Use was not significant ($\beta = 0.098$).

Multi-group invariance testing confirmed full equivalence across gender but only partial invariance across age. Teachers over 45 reported lower efficacy means (EF1 = 3.01 vs. 4.01; EF2 = 2.89 vs. 3.88), and the efficacy–satisfaction path was non-significant.

No significant differences were detected across educational stages. Invariance and non-parametric tests indicated that the structural relationships and item responses were consistent regardless of the school level in which teachers were employed. This finding suggests that the determinants of satisfaction with gamified applications operate similarly across pre-university stages, supporting the generalizability of the proposed model. Overall, the analysis highlights curricular alignment, efficacy, and robust feedback mechanisms as decisive drivers of teacher satisfaction with gamified educational applications.

Discussion

The present study investigated the determinants of teacher satisfaction with game-based educational applications, using a comprehensive analytical framework that integrates the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Information Systems Success Model (ISSM). While the majority of hypothesized relationships were statistically supported, one notable exception (Hypothesis H5) failed to demonstrate a significant direct relationship between curricular connection and perceived ease of use. This outcome invites a deeper conceptual exploration of the interaction between pedagogical alignment and usability. According to UTAUT (Venkatesh et al., 2003), facilitating conditions such as curriculum alignment are theorized to indirectly influence perceived ease of use by reducing barriers to technology integration. However, the present findings challenge this assumption, suggesting that strong curricular alignment may increase design complexity and cognitive load, particularly for teachers with limited digital proficiency. This observation aligns with prior research indicating that sophisticated, pedagogically robust features can paradoxically hinder usability (Zaharias & Poylymenakou, 2009; Alshammari et al., 2016). The study, therefore, underscores the need for a balanced, user-centered design approach that maintains pedagogical fidelity while ensuring interface simplicity. Moreover, the non-significant H5 relationship may be moderated by factors such as teachers' digital competence, experience with gamified tools, and instructional context. This aligns with the moderating effects proposed in the TAM extensions (King & He, 2006) and suggests that curricular connection alone is insufficient to enhance usability perceptions among less technologically confident educators. Incorporating these moderating variables into future models would allow for a more nuanced understanding of the interplay between pedagogical and technical dimensions in educational technology adoption.

Interestingly, the study's total effects analysis reveals that curricular connection exerts a strong indirect influence on satisfaction through learning efficacy. This finding supports the argument that curricular alignment functions primarily as a cognitive-affective enhancer rather than a direct usability driver. Teachers' perceptions of an application's alignment with curricular goals enhance their sense of instructional efficacy, which in turn amplifies satisfaction—a mechanism consistent with Bandura's (1997) social cognitive theory and its emphasis on self-efficacy as a determinant of motivation and satisfaction. In line with prior research (Al-Maroof & Al-Emran, 2018; Kim & Kim, 2017), the study confirms that perceived usefulness and perceived ease of use are critical predictors of attitude toward technology adoption, which subsequently influences learning efficacy and satisfaction. In this sense, Kim & Kim (2017), Matarirano et al. (2021) and Al-Maroof et al. (2021) detected perceived usefulness as an indicator of use in their respective studies. Although gamified apps can improve learning due to their portability, immediacy, adaptability, and interactivity, design determines their efficacy. The use of gamification by teachers will, therefore, be influenced by the perception they have of its efficiency; numerous studies demonstrate the efficacy of gamification in boosting student creativity, critical thinking, motivation, collaboration, and communication (Kingsley & Grabner-Hagen, 2015) in creating a better class atmosphere and improving student performance (González; Blanco, 2008; Fitz-Walter et all, 2011; Barata et Al., 2013; Li Et Al., 2013; González & Mora, 2014; Welbers et al. 2019). This sequential mediation pattern highlights the multifaceted pathways through which technical and pedagogical attributes interact to shape teachers' acceptance and satisfaction.

Furthermore, the results show that assessment and learning analytics significantly predict learning efficacy, emphasizing the importance of integrating feedback mechanisms

and data-driven insights into gamified applications (Ifenthaler, 2021; Choi et al., 2018). Studies by Walker (2011) and Clark et al. (2016) emphasize the importance of effective feedback that includes bifurcation based on students' answers and attention to partially correct answers, in other words, feedback that can redirect students towards the fully correct answer. It is also important that teachers can view how students use the app in order to t make decisions based on their efforts and progress within the app. Teachers value applications that facilitate personalized feedback and enable reflective learning, consistent with the literature on formative assessment and learning analytics in technology-enhanced learning environments.

The study's invariance analyses revealed notable age-related differences, particularly regarding the efficacy-satisfaction link, which was non-significant among teachers over 45 years. Studies by Joo et al. (2018) and Leem and Sung (2018) show that age was one of the most influential factors in perception of the use of innovative technologies. Although many studies suggest that teachers' age does not influence perception and use of gamification or technology, prior experience with active methodologies such as DGBL ultimately conditions a positive attitude in teachers (Fisher et al., 2014, Marín et al., 2020; Smith, 2018; Gómez-Carrasco et al., 2020). This finding suggests that older educators may have distinct motivational or experiential profiles that modulate their satisfaction with gamed tools, aligning with lifespan developmental perspectives on technology adoption (Morris & Venkatesh, 2000). Addressing these differences may require targeted interventions, such as age-sensitive training programs or interface adaptations, to foster inclusive technology integration.

Beyond statistical findings, the study contributes to educational practice by highlighting the need for a holistic approach to gamified application design. Developers should not only ensure alignment with curricular goals but also prioritize usability, adaptive feedback, and inclusivity. Moreover, institutional strategies should focus on enhancing teachers' digital competence and providing ongoing support to facilitate meaningful technology integration (Ertmer & Ottenbreit-Leftwich, 2010). In this sense, the adoption of a gamified app in the classroom must go beyond mere usage to become integrated in a systematized way that attends to the methodological principles that enable students to acquire content and competences that develop democratic values and attitudes (Pektas & Kepceoglu, 2019; Smith, 2018). Although many apps on the market link learning to gaming, their design is not necessarily based on suitable criteria for implementation in formal education, as noted by Kingsley and Grabner-Hagen (2015), Sánchez-Martínez and Ricoy (2017), Fombona-Cadavieco et al. (2020), and Vázquez-Ramos (2021). Professors and teachers find challenges in finding gamified resources, especially in digital format that correspond to different levels of the curriculum across various stages of education, or which can be adapted, or which present an inclusive design that facilitates the participation of all student users in the teaching-learning process, and which provide an enriching experience (Jedel & Palmquist, 2021). Educators report positive experiences with gamified apps in their daily practice when they are easy to use for both teachers and students, a finding consistent with prior studies highlighting ease of use as a decisive factor in the adoption of active methodologies or technologies (Sánchez-Mena et al., 2017; Buabeng-Andoh, 2021; Chocarro et al., 2021).

Furthermore, effective teacher training in gamification during pre-university education is essential. Professional development pathways should empower educators to integrate gamified methodologies coherently with curricular objectives, while fostering both sustainability awareness and ethical use of educational resources. Structured training that combines pedagogical principles, digital literacy, curriculum alignment, and ethical reflection ensures that gamified tools are not only engaging but also responsibly designed and

sustainably implemented. This approach aligns with findings by Triantafyllou, Georgiadis, and Sapounidis (2025), who emphasize that gamification is most effective when instructional-design principles ensure alignment with learners' needs and expectations (p. 503). Thus, establishing articulated training itineraries promotes both pedagogical efficacy and ethical, sustainable use in educational contexts.

The study has several limitations, including its cross-sectional design and reliance on self-reported data, which may be subject to bias. Future research should employ longitudinal designs and incorporate objective usage data to validate the observed relationships over time. Additionally, expanding the sample to include diverse educational contexts and cultural settings would enhance the generalizability of the findings. In conclusion, the study advances theoretical understanding by disentangling the complex relationships among pedagogical alignment, technical usability, and teacher satisfaction. It reinforces the view that educational technology acceptance is a multidimensional process shaped by both cognitive and affective factors.

Conclusion

The use of game-based educational apps is closely aligned with the pedagogical principles of mobile, ubiquitous learning and gamification. Increasingly, in-person education requires the integration of resources that support a variety of learning modalities (face-to face, blended, and remote) while incorporating elements that increase students' motivation to learn and facilitate feedback. In addition, the inclusion of digital devices and resources enables the development of diverse types of active methodologies such as the flipped classroom or problem-solving and challenge-based approaches. In this educational context, game-based learning apps promote mobile, ubiquitous learning of new concepts and competences, supporting and reinforcing content delivered in the classroom. They also increase opportunities for students to review material in a more motivational way.

Educational apps need to demonstrate a clear connection to the curriculum and be evaluated to address ethical and safety concerns. Teachers' adoption or non-adoption of these apps is largely determined by whether they provide support or develop concepts and competences within the curricular material. Although the number of apps available on Apple or Android systems is immense, the number of educational apps suitable for use in educational settings is limited, often due to teachers' lack of awareness, digital competence, or confidence in the use of digital resources. This research has analyzed the curricular factors that most influence the adoption or recommendation of a game-based learning app by teachers in primary education. The most crucial factor is that the app must be clearly aligned with curricular elements, such as content, competences, and education in values. Also, efficacy is predicted by the extent to which the challenges within the app correspond to the assessment criteria set out in the curriculum. Perceived ease of use was also identified as a predictor of teachers' attitudes toward using the game-based learning app. Finally, the investigation found no differences in terms of gender, but age differences were observed; teachers over 45 were less likely to perceive gamified educational apps as useful.

These results should inform the design of future apps, emphasizing that game-based learning apps should be developed by multidisciplinary teams that integrate technical, motivational, pedagogical, and disciplinary solutions. Educational authorities should provide a portal or repository for evaluated educational apps, enabling the identification of materials that effectively support curriculum development and incorporate gamification as a learning strategy.

Declarations

Ethics Statement

The research presented in this paper was carried out with the support of the Spanish Ministry of Science, through grant number RTI2018-099764-B-100.

All procedures followed were in accordance with the ethical standards of the responsible committee on human experimentation and with the Helsinki Declaration of 1975, as revised in 2000. Informed consent was obtained from all participants for being included in the study.

Conflict of Interest Statement

The authors declare that there are no conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Exploring the Relation Between Cognitive Presence, Self-Regulated Learning, and Learning Transfer: Insights From Medical Sonography Postgraduates

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Abstract
With the growing prevalence of online, flexible-delivery higher education programs, supporting students in developing higher-order thinking and the ability to apply theoretical knowledge in practical work situations poses a significant challenge for educators in health disciplines. This exploratory study aims to address the gap in empirical research on how higher-order thinking skills—cognitive presence, self-regulated learning, and learning transfer—interact to influence student learning in online environments. To investigate this, three survey instruments—measuring cognitive presence, self-regulated learning, and learning transfer—were combined into a single online survey questionnaire to evaluate their relationship. Participants are students from multiple courses in a medical sonography postgraduate program, with an online delivery. Their perspectives of their online learning environment are evaluated through quantitative and qualitative data. Responses from 89 out of 262 students (34% response rate) were analyzed using descriptive and inferential statistics and qualitative deductive analysis. Results suggest that students perceived stronger development in cognitive presence and learning transfer skills compared to self-regulated learning. Students perceived real-life case studies and presentations as the most relevant summative assessments for applying knowledge in the workplace. Qualitative data identified four themes related to the development of higher-order thinking skills that support learning transfer. Results show a statistically significant correlation between cognitive presence, self-regulated learning, and learning transfer. No significant differences were found across demographic groups in relation to the study variables, except for training hours per week. The key contribution of this study lies in offering an initial understanding of student perspectives on cognitive presence, self-regulated learning, and learning transfer in online environments. The limitations of this study point to areas requiring further research.

Keywords: Online learning; cognitive presence; self-regulated learning; learning transfer; medical sonography; allied health

Maranna, S., Joksimovic, S., Willison, J., Parange, N., & Costabile, M. (2026). Exploring the relation between cognitive presence, self-regulated learning, and learning transfer: Insights from medical sonography postgraduates. *Online Learning*, *30*(3), 269-296. https://doi.org/10.24059/olj.v30i3.5136

With the growing prevalence of online, flexible-delivery higher education programs, supporting students in developing higher-order thinking and the ability to apply theoretical knowledge in practical work situations poses a significant challenge for educators in health disciplines. While generic graduate attributes—such as communication, ethical practice, and lifelong learning—are recognized as transferable skills (Weng et al., 2024), ensuring students can transfer discipline-specific knowledge from the classroom to the workplace remains a critical concern. Efforts to bridge this gap are evident in innovations such as experiential learning (Hansen, 2008), authentic assessments (Herrington & Oliver, 2000), and work-integrated learning (Dean & Campbell, 2020; Kay et al., 2019).

Despite these initiatives, the assumption that students naturally transfer classroom learning to real-world problem-solving is often unfounded. Research highlights the need for deliberate integration of targeted learning tasks into course design to facilitate transfer (Kaiser et al., 2023; Wisneski & Ozogul, 2019). Additionally, effective transfer requires students to possess a degree of self-regulation. Studies have shown that students in online environments must assume greater responsibility for their learning than those in traditional face-to-face settings (Barnard et al., 2009; Broadbent & Poon, 2015). While prior research has established links between student self-regulation and higher-order thinking skills (Cassidy, 2011; Kuiper & Pesut, 2004), much of it does not focus specifically on online learning contexts.

In online learning, higher-order thinking is represented by the concept of cognitive presence within the widely used and researched Community of Inquiry (CoI) framework developed by Garrison et al. (2000) (Stenbom, 2018; Yu & Li, 2022). This study adopts the CoI framework as its theoretical foundation for evaluating cognitive presence, while also examining learning transfer and self-regulation within the context of online education. Although prior research (Broadbent & Poon, 2015; Cassidy, 2011; Garrison et al., 2010; Kuiper & Pesut, 2004; Maranna et al., 2022) indicates that cognitive presence, self-regulated learning, and the ability to transfer knowledge all contribute individually to student success, a preliminary literature review showed that their relationship is vastly unexplored. Moreover, recent studies by Maranna et al. (2025a) and Maranna et al. (2025b) highlight a significant gap: the lack of empirical research on the relationship between cognitive presence, self-regulated learning, and learning transfer in online environments. In response, this study aims to explore students' perspectives on these three variables to gain initial insights on how they collectively influence student learning in online settings.

Literature Review

Stone (2019) highlights several challenges faced in online learning by both students and educators, particularly regarding support for student learning. While the foundational principles of learning are similar across modes, online education differs significantly from face-to-face instruction (Stone, 2019). Supporting student-centered learning, which promotes higher-order thinking and real-world application of knowledge, requires distinct strategies in online environments (Archambault, 2022; Brandes & Ginnis, 1996). Higher-order thinking remains a vital twenty-first-century skill for futureproofing sustainable education and enables learners to have a collaborative, constructive influence to address evolving challenges and implement relevant changes to their context (Kumar, 2024; Golden, 2023; Scott, 2015). The main concerns for educators are the absence of dynamic face-to-face interactions and the need for a deeper understanding of online pedagogy to design tasks that promote these skills

effectively. From the students' perspective, the lack of face-to-face interaction can hinder collaborative, experiential learning, and the practical application of knowledge. Student success in online environments often requires a higher degree of self-regulation, which must be supported through intentional course design and active facilitation (Barnard et al., 2009). While the goal is for students to develop higher-order thinking skills and motivation to become lifelong learners, the responsibility rests with educators to design meaningful tasks, implement effective assessments, and facilitate relevant online educational experiences (Prince, 2004).

Research has shown that the educators play a key role in facilitating higher order thinking in online modes through design and instruction (Garrison et al., 2007). Research has also shown that students must take more responsibility for their learning in an online environment in comparison to face-to-face settings (Barnard et al., 2009). There is a substantial body of literature addressing various aspects of cognitive presence and SRL (Doo et al., 2023; Garrison, 2022; Shea & Bidjerano, 2009) and to a lesser extent their connection to learning transfer (LoGiudice et al., 2022). Studies have shown that the development of cognitive skills, including learning transfer, requires self-regulation (Barnard et al., 2009) and that it has a positive relationship with cognitive presence (Doo et al., 2023). Martins et al. (2019) studied learning strategies in an online corporate context and found a positive relationship between learning transfer with self-regulation and cognitive behavioral strategies. Similarly, a positive relationship was seen with the findings of a study conducted on school-aged students in traditional face-to-face settings (Oz & Sen, 2021). Barak et al. (2016) investigated the relationship between SRL and learning transfer in on-campus versus online students, finding that online students exhibited a greater degree of knowledge application and SRL skills. A study by Maranna et al. (2025a) explored the roles of cognitive presence and SRL on transfer in health-related online learning contexts. Their results showed that cognitive presence and online self-regulation strategies were positively correlated, meaning that students who were able to self-regulate their online learning demonstrated enhanced cognitive presence. These findings align with previous research suggesting that self-regulated learning has a positive effect on cognitive presence (Doo et al., 2023; Shea & Bidjerano, 2012). Shea and Bidjerano (2012) found that Integration and Resolution are specific aspects of cognitive presence related to learner self-regulation in online environments. Similarly, Johnson and Davies (2014) suggested that a key cognitive process for students in online environments is planning, which involves time management, regulation of effort and selecting relevant strategies to achieve their personal goals. The study by Maranna et al. (2025a) further demonstrated that increased cognitive presence increases students' ability to apply learnt knowledge. While evidence in literature (Broadbent & Poon, 2015; Cassidy, 2011; Kuiper & Pesut, 2004; Martins et al., 2019) has shown that cognitive presence, SRL, and knowledge transfer each play a role in student success, the constructs are mostly studied in isolation, providing limited insights into how cognitive engagement and self-regulatory processes interact to support transfer in online and blended clinical education contexts. Their interrelationship remains largely unexplored in applied health professional and clinical contexts, where the transfer of knowledge to practice is critical. Investigating this relationship is essential to inform the design of educational interventions that promote not only learner engagement, but also effective and sustained transfer of learning to clinical practice. This study addresses this gap by exploring how these constructs interact in applied clinical education, providing evidence for a holistic view of online learning in supporting student learning.

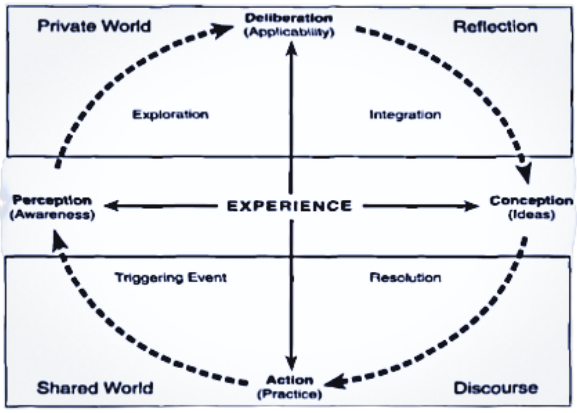
Community of Inquiry and Cognitive Presence

The CoI framework (Garrison et al., 2000) identifies three essential interdependent dynamic presences that contribute to a successful educational experience in online higher education (Garrison, 2022; Stenbom, 2018). These are teaching presence, social presence, and cognitive presence. Teaching presence is "the design, facilitation, and direction of cognitive and social processes to achieve personally meaningful and educationally valuable learning outcomes" (Garrison et al., 2000). Social presence is "the ability of CoI participants to project themselves socially and emotionally as real people within their communication medium" (Garrison et al., 2000). Cognitive presence is "the extent to which participants in any particular configuration of the CoI can construct meaning through sustained communication" (Garrison et al., 2000, p. 89).

Although the three presences overlap, the focus of our research is on cognitive presence as it informs how students develop a sense of inquiry, exchange information, connect ideas, and apply new information (Garrison, 2007). In other words, cognitive presence is central to students' critical thinking and focused on constructing personal meaning and shared understanding (Garrison, 2022) and consists of four phases (Garrison et al., 2000). The first phase is triggering, where a problem is identified, sparking the inquiry process. The second phase is exploration, during which students investigate relevant information, either individually or collaboratively with their peers. The third phase is integration, in which students construct meaning from generated ideas and share these within the community. The fourth phase is resolution, where students apply or defend potential solutions to problems using new ideas (see Figure 1). Triggering and exploration embody the initial levels of cognitive presence, while integration and resolution represent the higher levels, where students build on each other's ideas and synthesize information to provide real-world solutions (Garrison et al., 2001). The resolution phase as learning transfer is an implied concept and is underexplored. There are no evaluation methods in CoI except from coding. Course grades and performance data may be useful and needs further research (Maranna et al., 2025a).

Figure 1

The Practical Inquiry Model for Cognitive Presence (Garrison et al., 2001)



Self-regulated Learning

Self-regulated learning (SRL) refers to a learner's ability to select and implement effective strategies to achieve desired academic outcomes, informed by feedback on their learning effectiveness (Zimmerman & Martinez-Pons, 1990). SRL involves how students systematically activate and sustain their cognitions, motivations, and behaviors to attain their goals (Schunk & Greene, 2017). These behaviors include but are not limited to goal setting, time management, task strategies, environmental structuring, and seeking assistance. Success in online environments requires students to be self-disciplined and motivated, particularly in managing their time and completing tasks independently. Prior research indicates that students who do not exhibit SRL behaviors often struggle in online settings (Azevedo, 2005). A systematic review by Broadbent and Poon (2015) further supports this, revealing a positive relationship between SRL strategies and online academic success. Their analysis of nine SRL strategies found that metacognition, time management, effort regulation, and critical thinking were particularly influential in promoting academic success (Broadbent & Poon, 2015). SRL played a pivotal role in the development of cognitive skills, including learning transfer (Barnard et al., 2009). More recently, Doo et al. (2023) found that SRL is positively associated with cognitive presence. Research has suggested that SRL is a critical skill for students to succeed in online settings (Wang 2013; Wijekumar et al., 2006). Online learning differs from face-to-face learning, where students determine the location, time, and duration to access the learning materials (McMahon & Oliver, 2001) and must take more responsibility for their learning while not physically present in a classroom (Wang, 2013). Research on SRL before 2015 was predominantly in face-to-face settings (Pintrich, 2004; Richardson et al., 2012; Schunk & Pajares, 2002). Broadbent and Poon (2015) found that it often assumed students apply SRL strategies similarly—and with equal effectiveness—in both online and face-to-face environments. However, their findings, along with those of other researchers (Broadbent & Poon, 2015; Cho & Shen, 2013) suggest otherwise. Broadbent and Poon (2015) emphasized that educators should not presume students can automatically demonstrate SRL skills to online settings, nor that simply moving traditional teaching content online will yield equivalent learning outcomes.

Learning Transfer

Learning transfer refers to the ability to apply knowledge and skills learned in one context to another (Perkins & Salomon, 1988). Assumptions about learning transfer suggest that instruction in a specific context can lead to mastery of a task, making it sufficient for learners to apply the acquired knowledge in practice (Perkins & Salomon, 1988). Hajian (2019) instead views learning transfer as an integrative process, where learners actively engage with appropriate instruction, guidance, feedback, and opportunities for social interaction and authentic experience. Research on learning transfer has been more extensively explored in professional organization contexts (Baldwin et al., 2017; Huczynski & Lewis, 1980). For organizational training, Huczynski and Lewis (1980) illustrate the interplay between course content, individual motivation, and work environment. Similarly, Baldwin et al. (2017) developed a framework for transfer that includes training input factors, training outcomes, and conditions that support transfer. With literature on organizational training, most reported interventions are brief and are typically limited to a few hours and delivered as a single event (Thalheimer, 2020).

There have been relatively fewer studies on learning transfer in higher education that propose ways to enhance transfer among students (Forrester, 2018; Lim et al., 2022). For example, Sibthorp et al. (2011) investigated learning transfer in students involved in an experiential education program and reported that active learning, time to practice tasks, goal setting, and extending learning beyond the classroom are crucial for enabling transfer. In this context, instructors play a key role in mediating transfer by offering support, serving as role models and delivering effective instruction (Sibthorp et al., 2011). Forrester (2018), in a study on music education, suggested that successful transfer is closely tied to the learning conditions created by the instructor, with deliberate and systematic instructional strategies through goal-oriented instruction. Literature in conventional face-to-face teaching indicates that skill transfer is best supported in courses that highlight the relevance of the skills being learned, teach the underlying theoretical concepts, and promote the transfer of knowledge across both academic and workplace settings (Stanos, 2017). Two studies have compared learning transfer between online and conventional settings. Hansen (2008) examined transfer in marketing courses and measured transfer using student grades. Online students scored higher when compared to on-campus students (Hansen, 2008).

In skill-based higher education, such as in health disciplines, it is crucial to design learning activities that foster students' ability to apply knowledge and skills to real-world scenarios (Dori & Sasson, 2013). Fischer et al. (2022) highlight a lack of empirical evidence on how to nurture skill development and transfer in online contexts. This gap may stem from the inherent complexity of evaluating and understanding the transfer process (Hajian, 2019; Perkins & Salomon, 1988).

Study Context

The postgraduate diploma in medical sonography in an Australian university is delivered entirely online. At this university, a course is a 20-week unit that includes two weeks of pre-teaching, 13 weeks of teaching, a two-week mid-semester break, one week of self-study and revision, and two weeks of the exam period. At the University, programs are offered as either graduate diplomas with eight courses or master's degrees with 12 courses. This study is contextualized to students in the postgraduate diploma and masters of medical sonography.

The program has four level 1 courses and four level 2 courses. The students in level 1 courses do not require mandatory traineeships. Successful completion of these courses is a pre-requisite to undertake level 2 courses. Level 2 courses, on the other hand, require students to be in mandatory industry traineeships. The students in this study are from four courses: obstetrics and gynecology, vascular sonography, musculoskeletal sonography, and clinical sonography portfolio (capstone course). Successfully completing these courses enables the students to gain a postgraduate diploma.

Students are geographically dispersed across the country and simultaneously engaged in industry traineeships alongside their part-time online coursework. Traineeship refers to paid on-the-job training with an employer, while studying, with a focus on hands-on work experience and application of theory in a real-world setting. These clinical traineeships take place across a range of settings, including public and private hospitals, as well as rural and remote clinics. Students are required to complete a minimum of 200 clinical training hours within each 20-week period, while enrolled in level 2 scanning courses. A total of 2000 clinical training hours must be accrued before progressing to the capstone course. The

students in this study were enrolled in level 2 courses, namely, obstetrics and gynecology, vascular sonography, musculoskeletal sonography, and clinical sonography portfolio. The courses within the program are designed in alignment to the CoI framework (Garrison et al. 2000), where cognitive presence is fostered through collaborative activities such as discussion forums and brainstorming sessions; complex problem-solving tasks and the use of real-world scenarios embedded in both in summative and formative assessments (Gijbels et al., 2005). As this study specifically focuses on cognitive presence, the analysis centers on learning tasks and course design elements across the program. The assessments in the program were designed to be authentic, extending students' skills and knowledge beyond the virtual classroom. Authentic learning tasks are those that reflect mirror real-world challenges and require students to apply knowledge and skills in practical, safe environments reflective of workplace scenarios (Ashford-Rowe et al., 2013). While a comprehensive mapping of tasks across all courses was outside the scope of this study, several common design features were identified. These include recorded synchronous sessions, participation in discussion forums, formative quizzes, diagnostic image interpretation tasks, guest lectures by industry experts, and problem-solving assessments based on real clinical scenarios.

The program structure—combining online delivery of authentic, work-relevant content with concurrent clinical traineeships—provided a rich, work-integrated learning environment. This context offered an ideal setting to investigate students' perspectives on cognitive presence, SRL, and learning transfer, and to understand how these elements contribute to their overall learning experience. Demographic variables, based on the participant context, are included to evaluate any significant differences on the constructs. The following research questions (RQ) guided the investigation:

RQ1: What are the student perspectives on cognitive presence, SRL, and learning transfer in an online medical sonography program?

RQ2: What is the relationship between cognitive presence, SRL, and learning transfer in an online medical sonography program?

RQ3: Are there differences in students' cognitive presence, SRL, and learning transfer based on age, gender, geographic location, traineeship duration, and weekly training hours?

Methods

Sample Characteristics

Participants were recruited based on inclusion criteria. To be eligible, students had to be enrolled in the general stream of the postgraduate diploma in medical sonography program and concurrently engaged in a clinical traineeship. Accordingly, the sample population comprised all 262 students enrolled in the general stream of the program between February to July 2024.

Survey Administration and Ethical Considerations

This project was approved by the University Human Research Ethics Committee. Participation in the study was clearly communicated as voluntary, and all responses were

collected anonymously. The survey was developed using Microsoft Forms, accessed through the primary author's password-protected Office 365 university account. The survey was distributed via email and remained open from June to August 2024.

Data Collection

Data collection was conducted through an online questionnaire designed to measure cognitive presence, SRL, and learning transfer. The three questionnaires were integrated into a single online survey that is shared in an open access site (Maranna et al., 2025c). The survey consisted of three sections. Section 1 collected demographic information through seven multiple-choice questions, covering course name, traineeship location, age, gender, and duration of traineeship. This section aimed to examine whether variables such as age, gender, traineeship location, training hours per week and traineeship duration had any impact on cognitive presence, SRL, and transfer.

Section 2 of the survey presented three questionnaires in a matrix-style format, each comprising Likert-scale items. A five-point scale was used for responses, where 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree. The first 12 items were drawn from the validated CoI questionnaire developed by Arbaugh et al. (2008) specifically to assess students' cognitive presence. These items were grouped into four phases of cognitive presence: Triggering, Exploration, Integration, and Resolution, with three items assigned to each phase. The subsequent 24 items were taken from the validated Online Self-regulated Learning Questionnaire (OSLQ), developed by Barnard et al. (2009). These items measured students' perceptions of six self-regulation strategies in online learning: goal setting, environment structuring, time management, help-seeking, task strategies, and self-evaluation. The final ten items focused on students' perspectives of learning transfer, as developed by Maranna et al. (2025b). These items were grouped into three thematic areas: course content (4 items), student characteristics (3 items), and external factors (3 items).

Section 3 of the survey included two multiple-response questions designed to gain deeper insight into how the online course supported the application of theoretical knowledge in practice. Participants were given a list of common learning tasks and resources used across all courses and asked to select those they found most helpful. These options included: formative learning tasks such as practice quizzes; online learning resources such as content lectures; summative assessments such as case scenarios and real-life practice scenarios; recorded lectures; discussion forum interactions and synchronous sessions. An "Other" option allowed respondents to elaborate on additional resources or tasks not listed. Additionally, section 3 included one open-ended question, which asked participants to describe a specific resource, activity, or assessment from the online course that they found most beneficial during their traineeship.

Statistical Analysis

To address RQ1, descriptive statistics were generated using IBM SPSS Statistics (Version 24) to analyze the ordinal Likert scale data from the online questionnaire. Agreement levels were reported as percentages to summarize student responses. In addition to quantitative analysis, qualitative data from the open-ended survey responses were analyzed using Lumivero NVivo (version 14). A deductive qualitative analysis approach was employed, using predetermined codes and themes from a study by Maranna et al. (2025b).

This method involved categorizing responses into predetermined themes to extract meaningful insights into how the online content supported learning transfer (Bingham, 2023).

To address RQ2, Spearman's rank correlation coefficient (rs) was calculated using IBM SPSS Statistics (Version 29) to evaluate the relationship between cognitive presence, online SRL, and learning transfer. Spearman's correlation is a non-parametric measure used to assess the strength and direction of association between two ranked variables. A perfect positive correlation is indicated by rs = 1.0, and a perfect negative correlation is rs = -1.0 (Zār, 2014). According to Akoglu (2018), correlation values between 0.1 and 0.3 are considered low, 0.3 to 0.5 moderate, 0.5 to 0.7 high, and values greater than 0.7 indicate a very high correlation.

To address RQ3, inferential statistical analysis was conducted using IBM SPSS Statistics (version 29). Non-parametric tests, specifically the Mann-Whitney U and the Kruskal-Wallis test, were employed to compare independent groups based on demographic variables including gender, age, location of training, duration of training, and training hours per week. These tests were chosen due to the ordinal nature of the data and non-normal distribution. The Kruskal-Wallis test operates under the null hypothesis that the samples are independent and drawn from the same distribution, meaning there is no statistically significant differences between groups. A p-value of less than 0.05 was used as the threshold for rejecting the null hypothesis (McKnight & Najab, 2010).

Results

Student Perspectives on Cognitive Presence, SRL, and Learning Transfer (RQ1)

Respondents were students from the level 2 courses of the postgraduate diploma program. A total of 89 students responded to the survey, resulting in a response rate of 34% (89/262). Descriptive statistics, including mean scores for each indicator of cognitive presence and SRL are presented in Table 1. Frequency distributions for levels of agreement across the three questionnaires—cognitive presence, SRL, and learning transfer—are shown in Figures 2 to 4. The overall mean score for cognitive presence was 4.25 (SD = 0.65), for SRL was 3.73 (SD = 0.92), and for learning, transfer was 4.37 (SD = 0.66), based on a five-point Likert scale where 1 indicated the lowest level of agreement and five the highest. These results suggest that students perceived stronger development in cognitive presence and learning transfer skills compared to SRL. Lower mean scores were observed for SRL items (see Figure 3) related to task strategy and help-seeking, indicating areas where students may have felt less confident or supported.

The third section of the survey included multiple response items designed to gain deeper insights into the online learning activities that supported students' ability to apply theoretical knowledge in practice. For responses to the question on online learning resources the most frequently selected resources were practice questions (80/89 respondents; 89.9%) and recorded lectures (78/89 respondents; 87.6%). Problem-solving case discussions based on real-job scenarios were highly valued by 65 respondents (73%) while synchronous interactive sessions were selected by 66 (74%), identifying them as helpful for knowledge application. Additionally, 47 indicated that they accessed the recorded synchronous sessions, 64 used the revision resources and 55 found the discussing forum interactions with educator useful for knowledge transfer. To the question regarding summative assessments that

contributed to knowledge application, students reported that case studies (n = 72), case presentations (n = 65), and online case scenarios (n = 65) involving real-job situations were particularly effective in supporting knowledge transfer. Online quizzes (n = 67) were also perceived as useful for learning and self-evaluation.

Table 1

Descriptive Statistics for the Three Questionnaires (N = 89)

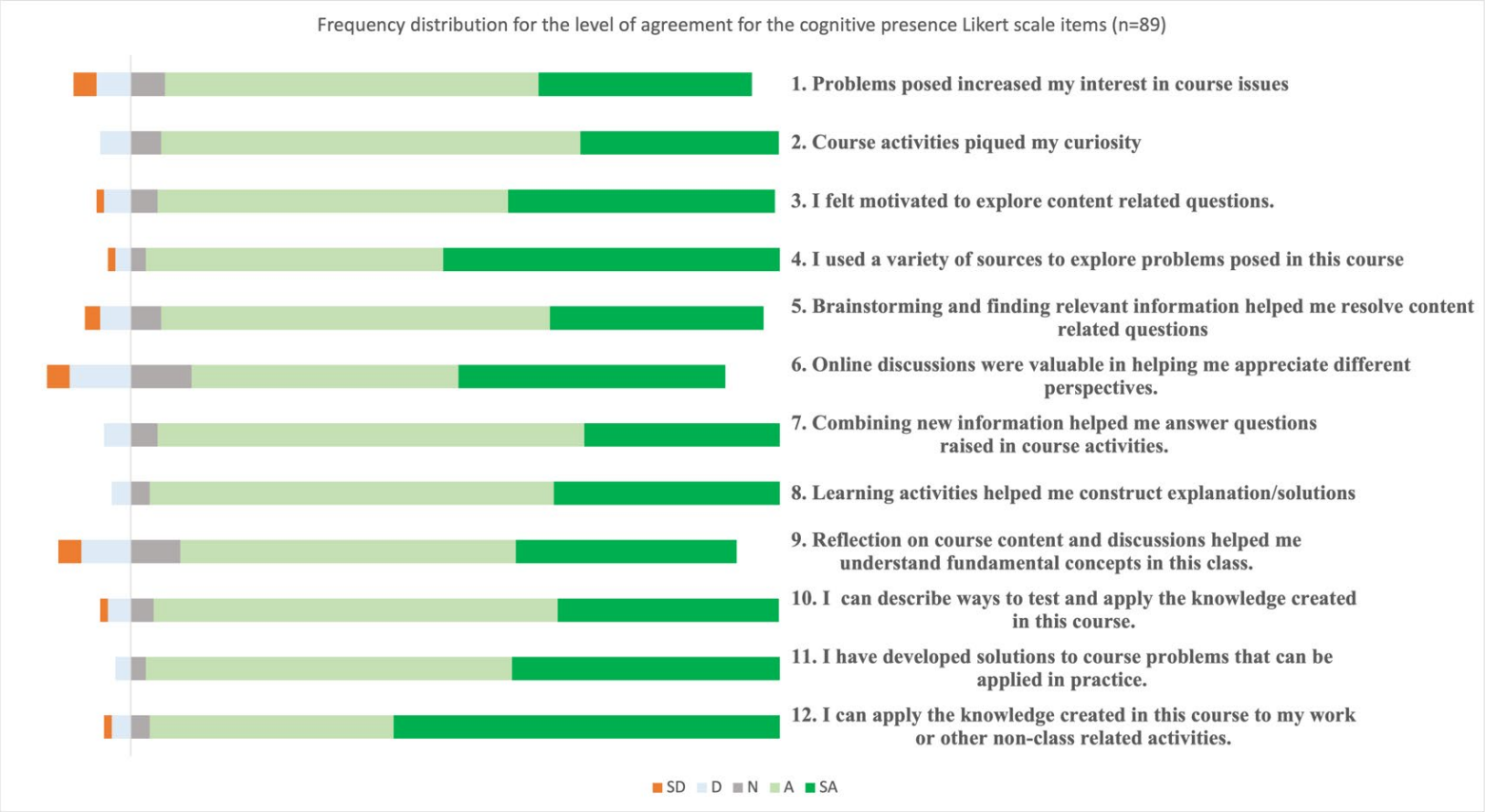
Indicator	Mean (SD)
Cognitive Presence	
Triggering	4.20 (0.68)
Exploration	4.25 (0.71)
Integration	4.20 (0.63)
Resolution	4.36 (0.61)
Overall Mean	4.25 (0.65)
Self-regulated Learning	
Goal setting	4.44 (0.66)
Environmental Structuring	4.35 (0.67)
Task Strategy	3.39 (1.07)
Time Management	3.64 (1.07)
Help Seeking	3.10 (1.08)
Self-Evaluation	3.49 (0.97)
Overall Mean	3.73 (0.92)
Learning Transfer	
Course content	4.42 (0.61)
Student characteristics	4.48 (0.55)
External factors	4.22 (0.83)
Overall Mean	4.37 (0.66)

Note. SD = Standard deviation

The open-text question invited participants to explain how a specific resource, activity or assessment from the online course supported their traineeship. A total of 60 out of 89 respondents (67.4%) provided written responses. Deductive coding (Bingham, 2023) using NVivo identified five main codes based on frequency of mention: (1) Lectures (n = 30); (2) Interactive online synchronous sessions (n = 24); (3) Formative learning tasks (n = 22); (4) Summative assessments (n = 15) and (5) Discussion forums (n = 4) These codes were then organized into four overarching themes related to the development of higher-order thinking skills that support learning transfer: (1) Conceptual understanding relevant to training, (2) Clinical reasoning, (3) Confidence and (4) Collaboration (Table 2). Additionally, several students mentioned the value of reading resources, such as textbook and study guides (n = 14), as well as real-time scanning videos (n = 6). One student highlighted the practical relevance of course content, stating, “All the information in the course applies to day-to-day scanning.” Recorded synchronous sessions were especially appreciated by students who often could not attend live sessions due to time zones differences and other scheduling constrains, underscoring the importance of flexible access to interactive content.

Figure 2

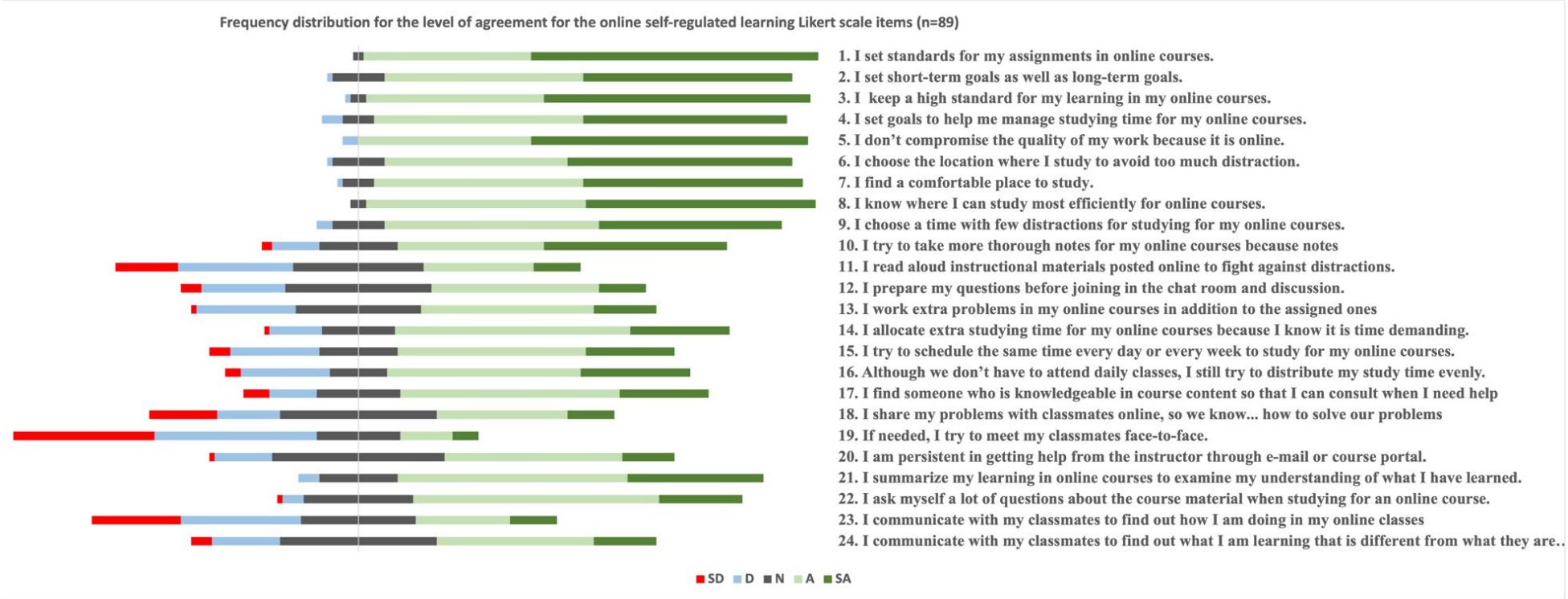
Descriptive Statistics of the Cognitive Presence Likert Scale Items



Note. SD = Strongly disagree; D = Disagree; N = Neutral; A = Agree; SA = Strongly agree.

Figure 3

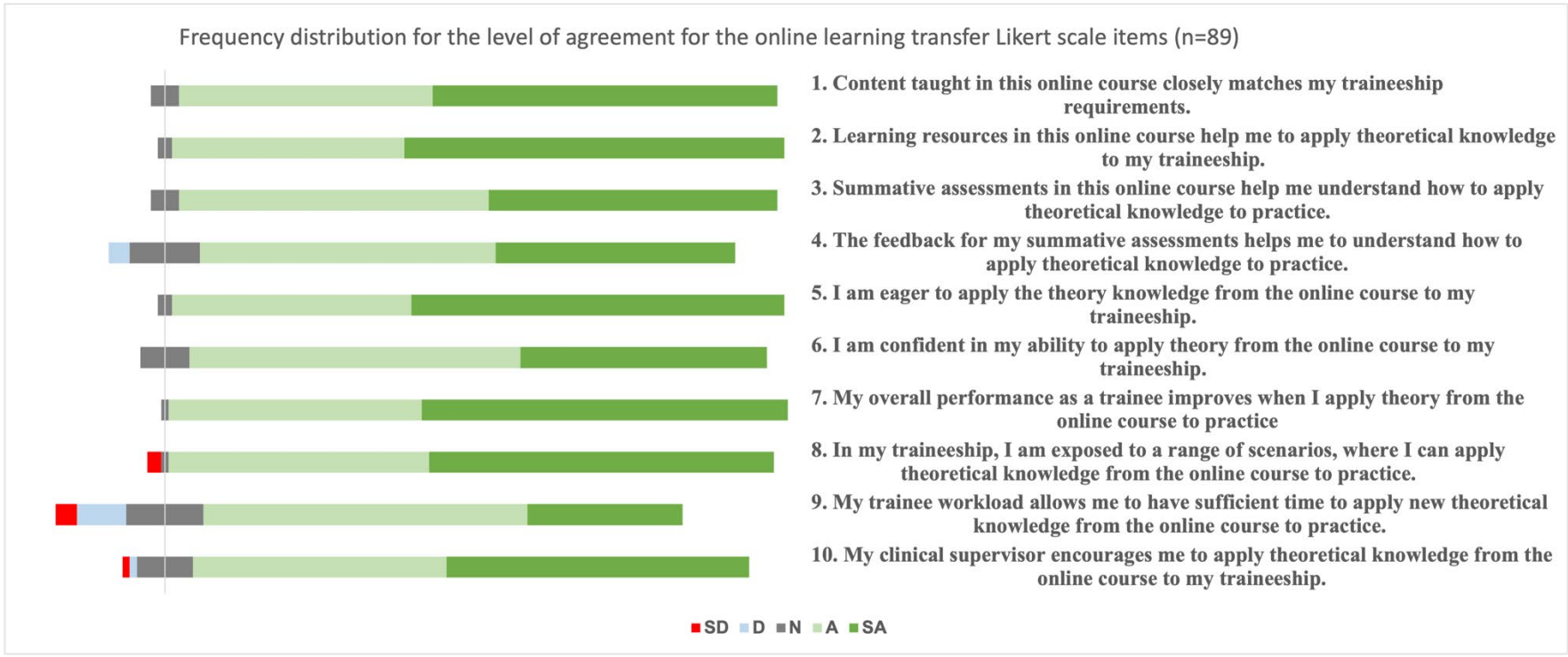
Descriptive Statistics of the Online Self-regulated Learning Likert Scale Items



Note. SD = Strongly disagree; D = Disagree; N = Neutral; A = Agree; SA = Strongly agree.

Figure 4

Descriptive Statistics of the Online Learning Transfer Likert Scale Items



Note. SD = Strongly disagree; D = Disagree; N = Neutral; A = Agree; SA = Strongly agree.

Table 2

Codes and Themes Derived from the Open-text Responses

Codes: Online content	Themes: How it helped in knowledge application
Lecture including lectures from guest experts (n = 30)	**Conceptual understanding relevant to training** Practical tips to optimize scans and to recognize pathology. Introduction to relevant concepts to support ongoing research and revision. Exemplar images and case scenarios to consolidate theory and interpret findings to explain pathology.
Interactive zoom sessions (n = 24)	**Conceptual understanding relevant to training** Practical tips on common pitfalls based on educators' clinical experience. Deeper insights to consolidate the content. Real-life scenario discussion with tips to tackle them at workplace. **Clinical reasoning** Case examples with diagnostic information and clinical reasoning to bridge the gap between theory and clinical practice. Provided a critical thinking atmosphere to enhance job skills. **Collaboration** To hear from peers made studying online less lonely.
Formative learning tasks (n = 22)	**Conceptual understanding relevant to training** To understand the reason for obtaining certain images, learn image description, correlate with clinical presentation and symptoms and propose differential diagnoses. Simulation helped to understand protocols and imaging planes. **Confidence** Reinforce learning and identify areas that need review, able to self-assess images effectively, and to familiarize with pathologies. **Collaboration** Discuss real life scenarios with industry supervisor and learn from the different approaches to the scenario.
Summative assessments (n = 15)	**Conceptual understanding relevant to training** Detailed investigation of specific topics relevant to the learning objectives and training requirements; solving real-world scenarios in a safe setting. **Confidence** Increased confidence in detecting pathology in the workplace.
Interactive peer discussion forum (n = 4)	**Clinical reasoning** For problem-solving and clarification **Collaboration** To compare how peers would approach the same problem and to improve knowledge application

Relationship Between Cognitive Presence, SRL, and Learning Transfer (RQ2)

Spearman's rank-order correlation (rs) test was performed using SPSS to examine the relationship between cognitive presence, SRL, and learning transfer. There was a significant positive correlation between cognitive presence and SRL (rs = .617, p = <.001, N = 89) and between cognitive presence and learning transfer (rs = .596, p = <.001, N = 89). There was a moderate positive correlation between SRL and learning transfer (rs = .445, p = <.001, N = 89) (Akoglu, 2018).

Differences in Student's Cognitive Presence, SRL, and Learning Transfer Based on Age, Gender, Geographic Location, Traineeship Duration, and Training Hours per Week (RQ3)

Of the 89 respondents, 70 (79%) identified as cisgender female and 19 (21%) as cisgender male, a distribution that is consistent with the broader Australian sonographer workforce (Australasian sonographers association, 2022). A Mann-Whitney U test was performed to examine whether cognitive presence, SRL, and learning transfer differed significantly by gender. The results indicated that females reported slightly higher cognitive presence (Mdn = 51.0) than males (Mdn = 49.0); while males reported marginally higher self-regulation (Mdn = 92.0) than females (Mdn = 90.5); For learning transfer, females (Mdn = 43.5) scored slightly higher than males (Mdn = 43.0). However, none of these differences were statistically significant: cognitive presence, U = 564, p = .313; SRL, U = 605, p = .548; and learning transfer, U = 664, p = .996.

All respondents were above 22 years of age, indicating that the participant cohort consisted entirely of adult students. Of the 89 respondents, 33 (37%) were aged 26–30, 25 (28%) were aged 31–35, 13 (14.6%) were aged 36–40, 11 (12.5%) were aged 22–25, and 7 (7.9%) were aged 41years or above. A Kruskal-Wallis test was conducted to examine whether age had a significant effect on cognitive presence, SRL or learning transfer. The results showed no statistically significant differences between age groups for any of the three variables: cognitive presence (df = 4, N = 89, p = .837); SRL (df = 4, N = 89, p = .923) or learning transfer (df = 4, N = 89, p = .392).

For the question on traineeship hours per week, five respondents trained for less than 15 hours per week, another five trained between 15 and 22.5 hours per week, 46 trained between 22.5 and 37.5 hours per week, and 33 trained for more than 37.5 hours per week. A total of 79 out of 89 respondents (88.7%) reported that they trained more than 22.5 hours per week. This aligns with the recommended clinical training guidelines set by the Australian Sonographer Accreditation Registry (2023). A Kruskal-Wallis test was conducted to examine whether weekly training hours has a significant effect on cognitive presence, SRL, and transfer. No significant difference was found in learning transfer across the training hour groups df = 3, N = 89, p = .070. However, significant differences were observed for cognitive presence df = 3, N = 89, p = .012 and SRL df = 3, N = 89, p = .011. Post hoc analysis revealed that students training 22.6 to 37.5 hours per week (Mdn = 51.5) reported significantly higher cognitive presence than those training less than 15 hours per week (Mdn = 43.0); Similarly, SRL was significantly higher among those training 22.6 to 37.5 hours per week (Mdn = 93.5; p = .013) compared to the less than 15 hours group (Mdn = 74.0; p = .007).

Regarding time since the commencement of traineeship, 15 respondents had been in training for more than 24 months, 21 for 19–24 months, 26 for 13–18 months, 10 for 7–12

months, 15 for 3–6 months, and two for less than 3 months. Overall, 72 out of 89 respondents (80.9%) reported having been in training for more than six months at the time of completing the survey. This suggests that most students had completed at least one clinical scanning course and were engaged in a second, as each course at the university spans 20 weeks. This is relevant, as students would have had substantial exposure to the online course content—including learning resources and both formative and summative assessments—allowing them to meaningfully assess its relevance to their clinical training. A Kruskal-Wallis test was conducted to examine whether the duration of traineeship had an impact on cognitive presence, SRL or learning transfer. The results showed no statistically significant differences across groups: cognitive presence ($df = 5$, $N = 89$, $p = .484$); SRL ($df = 4$, $N = 89$, $p = .604$); and learning transfer ($df = 4$, $N = 89$, $p = .444$).

Of the 89 respondents, 32 were training in New South Wales, 17 in South Australia, 13 in Western Australia, and eight in Queensland. Seven students each were training in Tasmania and Victoria, while two students each were from Northern Territory and Australian Capital Territory. One student was training overseas. A Kruskal-Wallis test was conducted to examine whether location has a significant effect on cognitive presence, SRL, and transfer. No significant differences were found across locations for cognitive presence $df = 8$, $N = 89$, $p = .746$; for SRL $df = 8$, $N = 89$, $p = .474$ and for learning transfer $df = 4$, $N = 89$, $p = .541$. This highlights the consistency in providing flexible course content options and their relevance to practice regardless of the training location.

Discussion

To the best of our knowledge, this study is the first to explore students' perspectives of cognitive presence, SRL, and learning transfer within a higher education health-related online environment (RQ1). Findings indicate a high level of agreement for both cognitive presence and learning transfer, and a moderate level of agreement for SRL (Figures 2 to 4). The overall mean scores were 4.25 (SD = 0.6) for cognitive presence, 3.73 (SD = 0.9) for SRL, and 4.37 (SD = 0.6) for learning transfer. The benefit of using self-report tools specifically designed for online environments is that it captures essential information about both the learner and the unique features of online settings. However, in the SRL questionnaire, three items demonstrated a relatively higher proportion of disagreement among respondents (see Figure 3). These were: Q11 (Task strategy)— "I read aloud instructional materials posted online to fight against distractions"; Q19 (Help seeking)— "If needed, I try to meet my classmates face-to-face"; and Q23 (Self-evaluation)— "I communicate with my classmates to find out how I am doing in my online classes". The lower agreement with these items may be attributed to the context of the postgraduate student cohort, who are geographically dispersed, professionally engaged, and are adult learners. Consequently, certain strategies such as in-person collaboration or verbal learning techniques may be less relevant in this setting.

Explicit information on learning tasks that enhance transfer was obtained. For instance, students reported that structured lectures, which first explained concepts and then allowed for the review and application of these concepts through real-life examples, were more effective for developing transfer skills than lectures that only explained concepts without providing examples. The findings also revealed that students found anecdotes used by educators to simplify and clarify complex concepts particularly useful. Additionally, formative tasks, such as online quizzes, were highly valued by students as they supported

conceptual understanding, practical application, and boosted confidence (See Table 2). This aligns with previous research on formative assessments. For example, Gikandi et al. (2011), in their review of online formative assessment in higher education concluded that such assessments provide immediate feedback and promotes engagement with critical learning processes. Say et al. (2022) propose that online quizzes provide immediate feedback and repeatability, enabling students to evaluate their understanding and improve performance. Koka et al. (2017), in their study, found that formative assessment enhances student skills in communication, collaboration, active participation, self-control, memory, and problem-solving. To enhance the usefulness of formative tasks, it is suggested to provide timely and immediate feedback (Gikandi et al., 2011) even if it is automated (Say et al., 2022). The online quizzes in the courses in this study had immediate automated feedback.

Summative assessments in the program were designed to be authentic and aligned with clinical training requirements, aiming to bridge theory and practice. Consistent with this design approach, students reported that case studies, case presentations, and online case scenarios involving real-job situations were particularly effective in supporting knowledge transfer, conceptual understanding. and boosting confidence in their workplace training (see Table 2). Students indicated that through these assessments, they gained foundational knowledge via research and felt better prepared to troubleshoot during their trainee jobs. This aligns with earlier studies that highlighted the benefits of problem-based learning (Duch et al., 2001; Gijbels et al., 2005) and authentic case studies (Maranna et al., 2023) in promoting student learning. Importantly, in these studies, the teacher's role as a facilitator, using real-world problems to stimulate student learning, was a key factor in students' success. Findings from the current study extends the advantages of such assessments for transfer of learnt knowledge to workplaces. Students reported increased autonomy and ownership when given the opportunity to choose case studies and projects relevant to their learning. This sense of ownership contributed to improved performance. This approach aligns with earlier research on SRL in traditional classrooms (Cassidy, 2011). Research in online environments further indicates that not all students are naturally inclined to self-regulate or demonstrate learning transfer; however, these skills can be developed through the intentional integration of teaching and learning strategies within course design (Broadbent & Poon, 2015).

For RQ2, analysis showed a significant positive correlation between cognitive presence and online self-regulation and between cognitive presence and learning transfer. There was a moderate positive correlation between SRL and learning transfer. This indicates that students who were able to self-regulate their online learning demonstrated enhanced cognitive presence, and students who had increased cognitive presence demonstrated an increased ability to transfer learnt knowledge. Integration and Resolution represent the higher levels of cognitive presence where learners build on each other's ideas and synthesize information to provide real-world solutions. Shea and Bidjerano (2012) claimed that Integration and Resolution are related to learner self-regulation in online environments. Past studies have shown that the development of cognitive skills, including learning transfer, requires self-regulation (Barnard et al., 2009) and that it has a positive relationship with cognitive presence (Doo et al., 2023). Several studies have established a link between SRL and critical thinking (Kuiper & Pesut, 2004; Phan, 2009). In the theoretical analysis, Phan (2009) emphasized that self-regulation plays a critical role in transforming students' cognitive abilities into tangible performance outcomes. Phan (2009) further suggested that critical thinking serves as a cognitive self-regulation strategy students use during learning. Research has also shown that cognitive presence and SRL share common components, such

as metacognition and motivation (Garrison, 2022; Shea & Bidjerano, 2009). Additionally, the ability to critically evaluate arguments and reasoning is vital for SRL (Oz & Sen, 2021). Moreover, cognitive presence and learning transfer are interconnected, particularly through the application of acquired knowledge (LoGiudice et al., 2022). Furthermore, since learning transfer involves applying knowledge gained in one context to another, it demands higher-order thinking skills and self-evaluation (Huang et al., 2015), particularly in assessing how a new situation influences performance.

The results in this study are supported by empirical evidence where links between SRL, cognitive presence, and transfer together underpin student success in online higher education (Maranna et al., 2025a; Martins et al., 2019; Oz & Sen 2021). Martins et al. (2019) found that SRL and cognitive-behavioral strategies positively influenced learning transfer in online corporate training, while Oz and Sen (2021) observed a similar relationship in face-to-face school settings. Barnard et al. 2009 and Zimmerman, 2002 found that SRL supports student learning by equipping them with the metacognitive, motivational, and behavioral strategies required to sustain engagement in online environments. These SRL strategies have been shown to also positively influence the development of cognitive presence, or the extent to which learners engage in critical reflection (Doo et al., 2023; Garrison et al., 2007). Cognitive presence, in turn, helps students to apply learnt knowledge, represented by the resolution phase in the CoI (Garrison et al., 2010; Perkins & Salomon, 1992). Collectively, from the evidence from the above studies and results of this study a learning pathway can be suggested: SRL enables students to engage effectively in tasks, cognitive presence reflects the quality of their meaning-making processes, and learning transfer demonstrates the successful application of these processes in real-world contexts.

RQ3 explored whether age, gender, geographic location, trainee duration, and training hours per week have any effect on students' cognitive presence, SRL, and learning transfer. Findings suggested that training 22.6 to 37.5 hours per week demonstrated more cognitive presence and SRL than those who trained for less than 15 hours per week. This aligns with the Australian Sonographer Accreditation Registry (2023) requirement of at least 22.5 hours of training per week for trainee students in the context of the current study. There was no significant statistical difference with other demographic groups such as age, gender, and location. This consistency suggests a sustained quality and effectiveness of the curriculum, regardless of student age, gender, geographical location, and duration of training. Existing literature on transfer primarily focuses on organizational training, where most interventions are brief—typically limited to a few hours and delivered as a single event (Thalheimer, 2020).

Implications for Teaching Practice

Several implications for teaching practice for enhancing cognitive presence, SRL, and learning transfer have stemmed from this study.

Educators' role is pivotal.

Educators' understanding, and implementation of effective teaching practices significantly shape students' development of cognitive presence, SRL, and learning transfer (Garrison et al., 2010; Yu & Li, 2022). For example, using questioning sessions as formative, non-graded activities can enhance learning by encouraging students to articulate and explore their understanding, rather than simply recall correct answers (Black & William, 2018).

However, it is the educator's responsibility to design questions that challenge common misunderstandings and promote collaborative problem-solving. To apply previously acquired knowledge in real-world practice, students must not only gain new information but also develop skills like problem-solving, collaboration, and self-regulation. Therefore, learning should be designed for acquisition of knowledge in diverse situations relevant to students' fields of study (Weng et al., 2024). It is also essential to leverage the influence of prior learning on current outcomes (Fauth & González-Martínez, 2021). Follow-up activities, such as reflection forums, can help consolidate and reinforce learning after training (Fauth & González-Martínez, 2021; Thalheimer, 2020). As shown in literature, tasks that require the applying concepts and integrating multiple related ideas are more effective than rote memorization (Agarwal, 2019).

Address design misconceptions about online learning.

Online environments were once considered unsupportive for students in applying knowledge to real-world situations, largely due to a lack of authentically designed learning tasks (Garrison, 2007). However, recent research and findings from this study indicate that this is no longer the case, as well-designed online tasks are now increasingly enabling meaningful knowledge (Maranna et al., 2022; Yu & Li, 2022).

Align curriculum with industry needs.

This is essential to promote learning transfer. This finding supports earlier research in organizational training (Lim & Johnson, 2002), where real-world relevance improved the transfer outcomes. Similarly, Fauth and González-Martínez (2021), emphasized that online training should be closely linked to industry demands and the learners' work environments. Incorporating real-work practice elements– such as simulating authentic conditions (Cano, 2015), using real-life examples in lectures, and facilitating interactive discussions– can significantly enhance learning transfer. To support this, educators should implement strategies that prompt students to reflect, think critically, and apply core principles to solve new and unfamiliar problems.

Adult learners' preferences in online education.

The participants in this study were adult learners, who typically adopt deep learning approaches, exhibit strong self-regulation and are intrinsically motivated to achieve their educational goals (Knowles et al., 2005). Reflecting these traits, participants valued learning tasks with real-life application and flexible asynchronous options. This finding aligns with prior research indicating that flexible access and job-relevant learning activities are critical to the academic success for adult students, many of whom balance study with family and career responsibilities (Kaiser et al., 2023).

Encourage concurrent learning and work application.

The findings from this study aligns with earlier research (Blume et al., 2010) indicating that learners who engage in concurrent training for an adequate period demonstrate greater skill transfer. In practical terms, this means that for effective transfer to occur in workplace –such as in obstetrics—students should be studying related content through their online courses while simultaneously applying it on the job. Communicating these insights to

industry supervisors and encouraging alignment between workplace training and online learning may improve transfer outcomes.

Design diverse learning experiences.

A balanced mix of synchronous and asynchronous learning appears to be most effective in online education. Asynchronous activities provide students with time for reflection and self-evaluation, while synchronous sessions enable collaboration, real-time feedback and brainstorming. Incorporating a variety of learning strategies—such as case studies, simulation-based learning, practical assessments (Maranna et al., 2022; Weng et al., 2024), experiential learning (Furman & Sibthorp, 2013), and formative assessments (Gikandi et al., 2011) –can significantly enhance cognitive presence, SRL, and transfer. Reflective practices, including self-assessment tasks (Cassidy, 2011) and collaborative learning, further support a "learning by doing" approach, which builds learners' confidence in their ability to transfer learning (Oz & Sen, 2021).

Limitations and Future Research

Generalizability is limited as the current study is contextualized to postgraduate medical sonography students and reflects their perspectives only. The participant context—where online courses were undertaken alongside workplace traineeships—was particularly well-suited for exploring student views on learning transfer. However, the findings should be interpreted with caution, as the postgraduate adult students are often intrinsically motivated to learn (Kaiser et al., 2023; Knowles, 2005), which may have influenced the outcomes. The study had a response rate of 34%, and like many survey-based studies in higher education, it may be subject to nonresponse bias—a known source of error that can skew results and limit generalizability (Standish & Umbach, 2019). Additionally, the dual role of the primary researcher as an educator in one of the courses introduces the potential for educator bias and perceived power hierarchy. This risk was minimized by recruiting students from five different courses and ensuring participation was both voluntary and anonymous. Since teaching presence was not the focus of research, common design elements—such as learning tasks and types of assessments—were listed and evaluated, regardless of the instructor for each course. Although this study did not assess the proportion of participants engaged in concurrent training, factors such as rostering difficulties, staff shortages, and limited trainee availability my hinder effective implementation of the model. Findings are only exploratory and clear causal links cannot be inferred from the correlational analysis.

Undergraduate student perceptions in both allied health and other disciplines with larger response rates need to be evaluated for a better understanding of the implications of course design. Keeping student equity at the center, ethical, and practical issues need to be considered, where pre and post-tests might be more feasible than case-control studies. Concurrent training models should be evaluated to gain empirical data. Evaluation of transfer using Kirkpatrick's model (Kirkpatrick & Kirkpatrick, 2006), using the four levels (reaction, learning, transfer, and results) should be explored. Similarly, another model is the Course Assessment for Skill Transfer by Fischer et al. (2022), a suite of conceptual tools to aid course designers, instructors, or external evaluators in assessing which essential skills are being taught and to what extent. The framework supports skills transfer from classroom to the workplace.

Conclusion

Given the limited research on learning transfer within online higher education, this study offers an initial understanding of student perspectives on cognitive presence, SRL, and learning transfer in online environments, and provides evidence on how these variables collectively influence student learning. While this study does not assess the causality of the relationship, the findings suggest that increased SRL enhances cognitive presence, which in turn improves transfer skills. However, the findings also highlight that learning transfer in online environments remains an underexplored area and warrants further research.

Declarations

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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. This project was approved by the University Human Research Ethics Committee, protocol number 205285.

AI Use Statement

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 authors, who take full responsibility for the accuracy and integrity of the work.

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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Evaluating TAM Validity and Reliability in Mobile Learning for Students with Disabilities in South African Distance Education

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Abstract
This study examined the psychometric properties of two primary domains: perceived usefulness (PU) and perceived ease of use (PEOU) in the technology acceptance model (TAM), and their value in determining mobile learning (m-learning) usage among a sample of 220 students with disabilities (SwD) enrolled in a distance education (DE) institution in South Africa. This appears to be one of the first studies in the country to establish internal consistency of the domains among SwD and confirm the two-factor structure using confirmatory factor analysis (CFA; χ^2/df = 2.26, CFI = .982, NFI = .969, IFI = .983; TLI = .971, SRMR = .039). These two constructs exhibited factor loadings (λ) ranging from .79 to .95 and produced a structure consistent with the original TAM (Davis, 1989). From a theoretical perspective, the CFA findings reinforce the construct validity of the TAM across various student populations while supporting its cross-cultural applicability in diverse educational settings. However, regression analyses suggested that PU and PEOU were not significant predictors of m-learning usage among SwD (β = .026, t = .300; p = .764; β = -.010, t = -.113, p = .910, respectively), warranting a critical review of the TAM among SwD in DE settings and giving credence to the notion that m-learning usage is deeply embedded in the structural realities of living with a disability and studying at a distance in South Africa. Nonetheless, this study contributes to the limited psychometric research on the TAM in the South African DE sector and establishes a foundation for understanding m-learning usage among SwD in developing contexts.

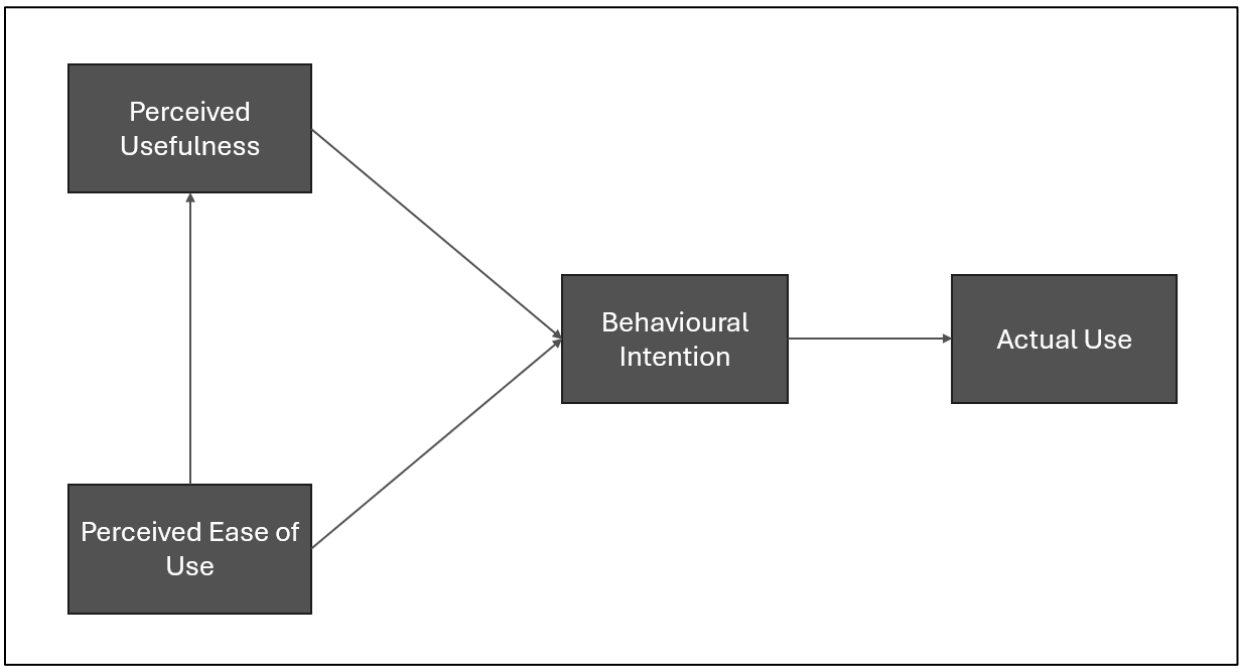
Keywords: Technology acceptance, students with disabilities, inclusive education, mobile learning, distance education, South Africa

Young, K. & Louw, A. (2026). Evaluating TAM validity and reliability in mobile learning for students with disabilities in South African distance education. *Online Learning, 30*(3), 297-318. https://doi.org/10.24059/olj.v30i3.5095

The Technology Acceptance Model (TAM), first developed by Davis (1985) and later refined by Davis (1989), has become one of the most influential frameworks for explaining information systems (IS) behaviour. Drawing on the Theory of Reasoned Action (Fishbein & Ajzen, 1975), which suggests that attitudes and subjective norms shape behavioural intentions (BI), the TAM postulates that acceptance of technology is predicted by users' BI, which is, in turn, determined by two core cognitive perceptions: the perceptions an end-user has towards the ease of use and the usefulness of the system (see Figure 1). Davis defined the latter, i.e., perceived usefulness (PU), as the degree to which the person believes that using a particular system would enhance performance, whereas the former, i.e., perceived ease of use (PEOU), is defined as the degree to which the person believes that using a particular system would be effortless. These two constructs are said to strongly influence the acceptance or use of a new IS or information technology (IT), a finding implied in the literature. Although the TAM has been extended to include social and contextual factors over the years (i.e., TAM2, Venkatesh & Davis, 2000; Unified Theory of Acceptance and Use of Technology, UTAUT, Venkatesh et al., 2003), the original TAM remains widely applied in diverse contexts due to its parsimony, explanatory power, and consistent empirical validation (Marangunić & Granić, 2015), and is thus explored in relation to mobile learning (m-learning) among students with disabilities (SwD) in the current paper.

Figure 1

The Technology Acceptance Model (Davis, 1989)



m-Learning Among SwD

M-Learning has emerged as a central modality in contemporary higher education due to its flexibility, accessibility, and potential to reduce longstanding participation barriers for diverse student groups (Gupta et al., 2021; Mustaffa & Mansor, 2015; Suner et al., 2019). Unlike

traditional e-learning delivered through desktop-bound systems, m-learning enables continuous, context-independent engagement with educational content through portable devices (Gupta et al., 2021; Murphy et al., 2014; Mustaffa & Mansor, 2015; Nichter, 2021), making it particularly valuable in settings where students have varied access to infrastructure and support (Lall et al., 2019; Milheim et al., 2021). In South Africa, where structural inequalities and resource constraints remain prevalent (Bozalek & Boughey, 2012; van Rooyen & Marais, 2018), mobile technologies often serve as students' primary means of accessing online materials, communication tools, and learning platforms (van Rooyen & Marais, 2018). For SwD, m-learning offers additional benefits, including the use of built-in accessibility features (e.g., screen readers, magnification tools, gesture-based navigation) and the ability to personalise the learning environment to meet individual functional needs (Ayoola & Mangina, 2012; Ciampa, 2014). Given these affordances, examining TAM within an m-learning context is both appropriate and necessary; the constructs of PU and PEOU become especially relevant when technology may either mitigate or exacerbate accessibility challenges (Kim et al., 2020; Lall et al., 2019).

A Chronological Review of the Psychometric Properties of the TAM's Core Constructs

Reliability

Since 1989, the psychometric properties of the TAM have been explored across various settings and populations. In the earliest of these, Davis (1989) established support for the internal consistency of the model's core constructs using various ISs (i.e., PROFS electronic mail, XEDIT file editor, Chart-Master, and Pendraw). Results from these seminal explorations revealed Cronbach's alpha coefficients (α) ranging from .91 to .98, attesting to the reliability of the constructs when applied to a diverse range of technological contexts. Since then, numerous studies have reported on the internal consistency of these core components, all of which have yielded satisfactory Cronbach's alphas ($\alpha > .70$) across various ISs and samples, as shown in Table 1 below.

Table 1

Cronbach's Alpha Coefficients of PU and PEOU

Study	Technology	PU	PEOU
Davis (1989)	PROFS electronic mail; XEDIT file editor	.97	.91
Davis (1989)	Chart-Master; Pendraw	.98	.94
Adams et al. (1992)	Email	.94	.88
Adams et al. (1992)	Voice mail	.93	.81
Chau (1996)	Microsoft Word	-	.93
Chau (1996)	Microsoft Excel	-	.94
Masrom (2007)	e-Learning system	.89	.89
Šumak et al. (2011)	Moodle	.82	.90
Ameri Shahrabi et al. (2013)	-	.89	.87

Wong et al. (2013)	Computers	.87	.97
Tarhini et al. (2013)	Blackboard	.91	.90
Bere and Rambe (2016)[a]	WhatsApp	.86	.87
Almaiah and Alismaiel (2019)	m-Learning	.85	.86
Rafique et al. (2020)	Insignia ILS	.93	.97
Pamela and Rahman (2021)	m-Learning	.79	.80
Qashou (2021)	m-Learning	.81	.77
Zhou et al. (2022)	Online education platform	.92	.87
Humida et al. (2022)	e-Learning system	.88	.77
Şahin et al. (2022)[b]	e-Learning system	.94	.91
Kabir et al. (2023)[b]	Assistive mouse controller (AMC)	.72	.79
Şahin et al. (2023)	Assistive technologies (ATs)	.84	.77
Tawafak et al. (2023)	e-Learning system	.91	.93
Kampa (2023)	m-Learning	.97	.96
Şahin and Yıldız (2024)[b]	m-Learning	.96	.95

[a] South African study; [b] Sampled SwD / Special needs; - not reported.

Construct Validity

In the seminal validation of the TAM, Davis (1989) established support for the construct validity of the dimensions using a factor- and multi-trait-multi-method (MTMM) analysis. Using a sample of 112 users from a software development company, results revealed that the items loaded distinctly onto the two aforementioned factors, a finding corroborated in a follow-up study by Davis (1989) and another by Adams et al. (1992). It was not until a year later that confirmatory factor analyses (CFA) were used to explore the validity of the scales. Using Adams et al.'s (1992) data, Segars and Grover (1993) initially reported poor fit indices (cf. Hu & Bentler, 1999) but acceptable fit after respecifying PU into usefulness and effectiveness. A similar modified TAM was examined by Chau (1996), who reported satisfactory indices (χ^2/df = 1.44, GFI = 0.94, AGFI = 0.90, NFI = 0.96, NNFI = 0.98, CFI = 0.99) among a sample of 192 Microsoft Word users and 176 Microsoft Excel users.

Later studies examined the validity of the TAM in diverse educational technology contexts. Among these, Masrom (2007) found support for the original two-factor structure among 122 e-learners in Malaysia using exploratory factor analysis (EFA) with factor loadings (λ) ranging between .60 and .77, as did Šumak et al. (2011), who revealed strong factor loadings (λ = .72 – .90) and acceptable fit indices for PU and PEOU among 235 Moodle students in Slovenia. Consistent evidence of construct validity has also been reported in developing countries, including Iran, South Africa, Lebanon, and Malaysia (Ameri Shahrabi et al., 2013; Bere & Rambe, 2016; Tarhini et al., 2013; Wong et al., 2013), providing additional corroborative evidence on the validity across different cultures.

More recently, Rafique et al. (2020) confirmed the measurement model using data from 340 university students in Pakistan. Similar to the results noted above, the measurement model attested to the model's construct validity and proved fruitful in determining BI to use a mobile library application (i.e., Insignia ILS). Zhou et al.'s (2022) study also explained substantial

variance (68.6%) in 276 university students' BI to use an online learning platform in China (λ = .83 – .91), as did Şahin et al. (2023), who extended the TAM to assistive technologies (ATs) and found that PU and PEOU exhibited robust factor loadings (λ = .76 – .85). PU and PEOU along with others in the model (i.e., self-efficacy, facilitating conditions, compatibility, enjoyment, anxiety, social influence, and personal innovativeness) accounted for 57.9% of the variance in BI to adopt ATs.

Limited Psychometric Findings Among SwD using m-Learning

Notably absent from the discourse above is the validation of the TAM among SwD or individuals with special needs, as well as its applicability to m-learning, from both a construct and predictive perspective. Although Oladejo et al. (2018) explored m-learning among SwD and its acceptance thereof, the psychometric properties are confined to a reliability index of the instrument, with no mention of validity among the said sample. It was not until a couple of years later that scholars began exploring the psychometric properties of the TAM among SwD (or special needs). Around this time, Şahin et al. (2022) sampled 1,713 university students with special needs in Turkey. Their sample was asked to rate their perceptions of using an e-learning system at the institution. In addition to the core constructs in the TAM, the authors included self-efficacy, compatibility, social influence, facilitating conditions, perceived enjoyment, and anxiety in the model. Results corroborated previous findings in the field, attesting to the reliability and validity of the core constructs (λ = .84 – .93) and, in combination with the other constructs, explained 76.9% of the variance in BI to use the e-learning system. Most recently, Şahin and Yıldız (2024) sampled 1,298 university SwD enrolled in a distance education (DE) program and ascertained the reliability and validity of the core constructs as they relate to a student's BI to adopt m-learning. Using a CFA, the authors revealed that the two core constructs in the TAM exhibit strong validity among SwD pursuing their studies at a distance (λ = .89–.95). Overall, the model (with additional constructs) explained 76.5% of the variance in SwD's BI to adopt m-learning.

The (Over) Emphasis on Behavioural Intention

The literature which concerns itself with the TAM and IS usage relies heavily on BI as a mediator, despite context, sample, or IS. While undoubtedly as a consequence of *a priori* assumptions inherent in foundational theories of human behaviour (Bandura, 1971; Fishbein & Ajzen, 1975), the overemphasis on BI limits the theory's applicability to determining actual system use. As Conner and Norman (2022) rightly indicate, measures of BI (which commonly include both a valence and an extremity component) "rarely predict all or even the majority of the variance in behaviour" (p. 2).

In an attempt to narrow this gap, a handful of scholars have explored various antecedents with direct paths to actual m-learning usage (Almaiah & Alismaiel, 2019; Althunibat et al., 2021; Alyoussef, 2021; Drwish et al., 2023; Lutfi et al., 2022; Wu et al., 2025). In the earliest of these studies, Almaiah and Alismaiel (2019) and Althunibat et al. (2021) found that satisfaction was a significant predictor of m-learning usage among university students in Jordan (β = .610, p < .001; and β = .527, p < .001; respectively). Similar results were reported by Lutfi et al. (2022), who also revealed that satisfaction was a significant factor influencing m-learning usage among university students in Saudi Arabia (β = .569, p < .001). More recently, Drwish et al. (2023) suggested that system quality (β = .320, p < .001) and service quality (β = .164, p < .001) are

significant drivers of m-learning usage, along with satisfaction ($\beta = .683$, $p < .001$). In terms of the two core constructs of the TAM (PU and PEOU), only a couple of researchers have explored these direct paths to actual m-learning usage (Drwish et al., 2023; Wu et al., 2025), both of whom have reported significant betas among university students in Saudi Arabia and China, respectively. Lamentably, these findings remain confined to traditional university students abroad, precluding any generalisability to the South African DE context.

Aim and Objectives

Given the aforementioned, the core concepts inherent in the TAM, which reportedly influence m-learning usage (PU and PEOU), should be explored and validated among SwD in a DE setting in South Africa. In doing so, indices of reliability and (construct and predictive) validity can be established, inform future praxis among similar samples, and serve as a basis for comparing studies in other developing (and developed) countries. In line with the broad aim, the research objectives are as follows:

1. To determine the extent to which the core constructs of the TAM are reliable among SwD in relation to m-learning

2. To determine the extent to which the core constructs of the TAM are valid among SwD in relation to m-learning, and

3. To determine the extent to which the core constructs of the TAM predict m-learning usage among SwD.

Methods

Research concerning vulnerable populations such as SwD needs to adhere to ethical protocols with a strong emphasis on informed consent, autonomy, and the minimisation of harm (Brown, 2015; McDonald & Kidney, 2012). As such, the anonymity and accessibility of the online questionnaire decreased the possibility of coercion while increasing participant comfort, which is essential when engaging with marginalised groups (Young-Pelton & Dotson, 2017). In addition to adhering to these ethical principles, clearance for this study was obtained from the institution's Department of Psychology and the College of Human Sciences' Ethics Committee (Ref #: 2020-PsyREC-67141242). In addition, research permission to involve SwD was granted by the institution's Research Permission Sub-Committee (RPSC; ref #: 2020_RPSC_024).

Thereafter, using a cross-sectional design and a census sampling technique, a brief explanation of the study and an invitation to the online survey were distributed via institutional email to all SwD at a South African DE institution in the 2023 academic year (N = 2,808). This was achieved by enlisting the assistance of the ICT department at the respective institution. The survey was administered in English and included demographic items, the TAM's core constructs (i.e., PU and PEOU, see Appendix A) and an item on m-learning usage (i.e., "How often do you use m-learning for your studies?"). Inclusion criteria required participants to be registered SwD and 18 years or older; exclusion criteria comprised non-consent, age below 18, or incomplete responses. Of the 247 students who started the survey, 27 were excluded due to substantial missing data. The sample consisted of individuals who completed the online survey within the allotted time and met the criteria, comprising 220 participants (n = 220), resulting in an overall response rate of 7.8%.

Participants

Demographics

Of the 220 SwD who constituted the sample, most were female (n = 148; 67.3%), undergraduate students (n = 175; 79.5%), African (n = 130; 59.1%), and reported English as their home language (n = 50; 22.8%). These frequencies, along with other descriptive statistics, are presented in the table below.

Table 2

Demographic Characteristics of the Sample (n = 220)

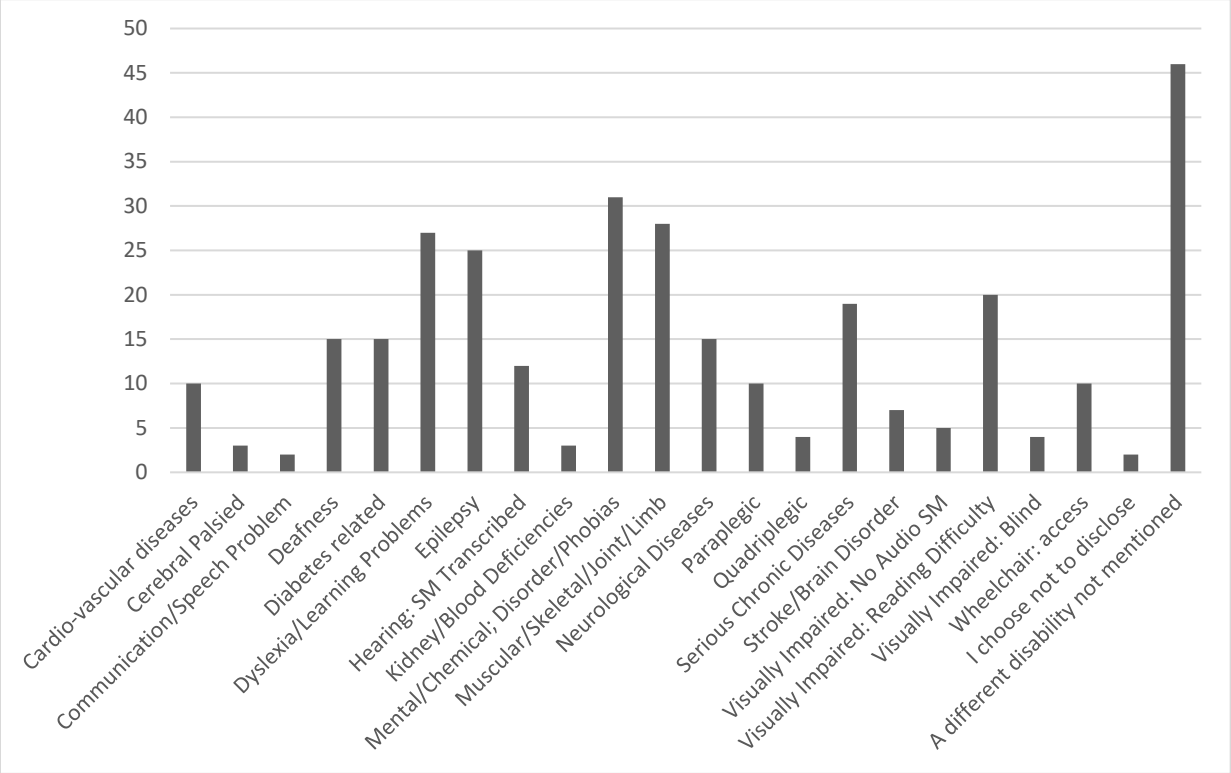
Variable	Category	*n*	%
Gender	Female	148	67.3
	Male	66	30.0
	Other / Not specified	6	2.7
Age	Range = 19-66 years ($\bar{x}$ = 33.7; SD = 10.6 years)	220	100.0
Level of study	Undergraduate	175	79.5
	Postgraduate	45	20.5

Variable	Category	*n*	%
Ethnicity	African	130	59.1
	White	63	28.6
	Mixed race	14	6.4
	Indian	11	5.0
	Other	2	0.9
Language	English	50	22.8
	isiZulu	38	17.4
	Afrikaans	37	16.9
	isiXhosa	17	7.8
	Other languages	78	35.1

Regarding the various disabilities, most of the sample indicated that their disability was not mentioned in the dropdown list contained in the online survey (20.9%; $n = 46$). Other participants noted mental or chemical disorders or phobias (14.1%; $n = 31$), followed by those who indicated a muscular/skeletal/joint/limb disability (12.7%; $n = 28$) and dyslexia or other learning problems (12.3%; $n = 27$). Less frequently reported among the sample were communication or speech problems (0.9%; $n = 2$), cerebral palsy (1.4%; $n = 3$), and/or blood/kidney deficiencies (1.4%; $n = 3$). These and other frequencies are graphically depicted below (see Figure 2).

Figure 2

Disabilities Reported Among the Sample (n = 220)



m-Learning Usage

Of the 220 SwD who comprised the sample, 147 students (66.8%) reported using m-learning daily, while 51 students (23.2%) indicated that they used it every few days. Cumulatively, eight students in the sample used mobile devices for learning once a month (1.4%; $n = 3$) or once every few months (2.3%; $n = 5$). These frequencies, along with others, are listed in Table 3 below.

Table 3

Frequency of m-Learning Usage Among the Sample

	n	**%**
Daily	147	66.8
Every few days	51	23.2
Once a week	10	4.5
Once every couple of weeks	4	1.8
Once a month	3	1.4
Once every few months	5	2.3
Total	**220**	**100.0**

Data Analysis

Following the analysis of demographic characteristics, reported disabilities, and m-learning usage, the reliability of the two constructs was tested using Cronbach's alpha and composite reliability coefficients. The measurement model of the original two-factor solution put forth by Davis (1985) was then computed and confirmed using a CFA, followed by a regression analysis, which sought to ascertain predictive validity. These analyses were performed in SPSS (version 28) and AMOS (version 29) and are presented below.

Reliability

The internal consistency of the PU and PEOU domains was assessed using Cronbach's alpha and composite reliability coefficients. Results revealed that both PU and PEOU were reliable among the sample of SwD (n = 220), yielding Cronbach's alphas (α) of .95 and .91, respectively. Further evidence of internal consistency was provided by calculating composite reliability coefficients, which were identical to the reported Cronbach's alphas and demonstrated acceptable levels of reliability (i.e.,> .70). These results are presented in Table 4.

Table 4

Reliability Coefficients of the Measurement Model

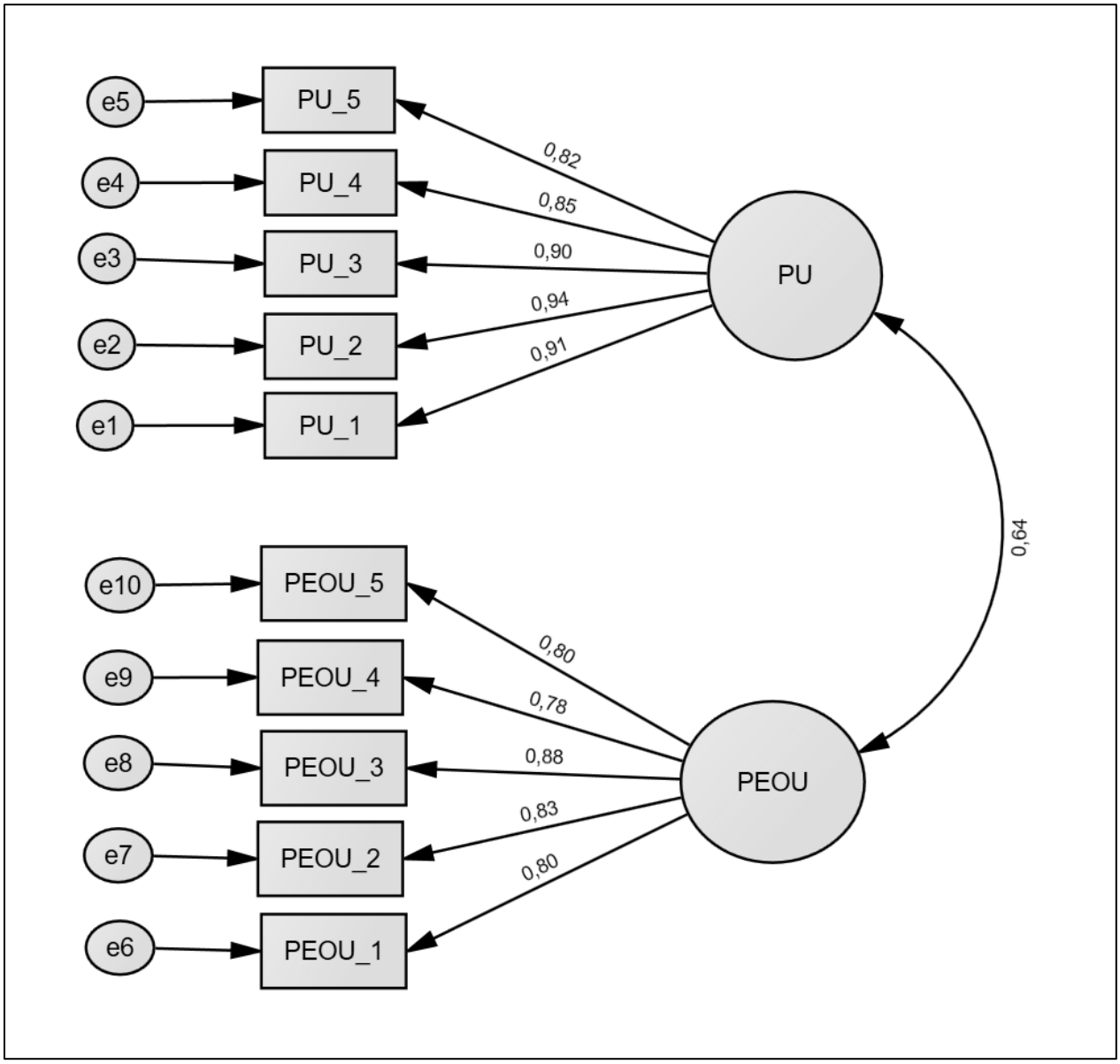
Construct	Number of items	Cronbach's alpha (α)	Composite reliability
PU	5	.95	.95
PEOU	5	.91	.91

Confirmatory Factor Analysis (CFA)

As mentioned, a CFA was performed using AMOS (version 29) to test the measurement model and assess the construct validity of the two constructs in the TAM. As part of the CFA, factor loadings (λ) were evaluated for each item, ranging from .78 ("It is easy to use m-learning to accomplish my study tasks") to .91 ("I believe that m-learning enhances my academic performance"). Moreover, the model-fit indices used to assess the model's overall goodness of fit (χ^2/df, CFI, NFI, IFI, TLI, SRMR) fell within acceptance levels (Hu & Bentler, 1999) and suggested that the two-factor solution (consisting of PU and PEOU) yielded a good fit to the data; χ^2/df = 4.17, CFI = .945, NFI = .929, IFI = .945; TLI = .927, SRMR = .051. This two-factor measurement model and the standardised estimates are depicted below.

Figure 3

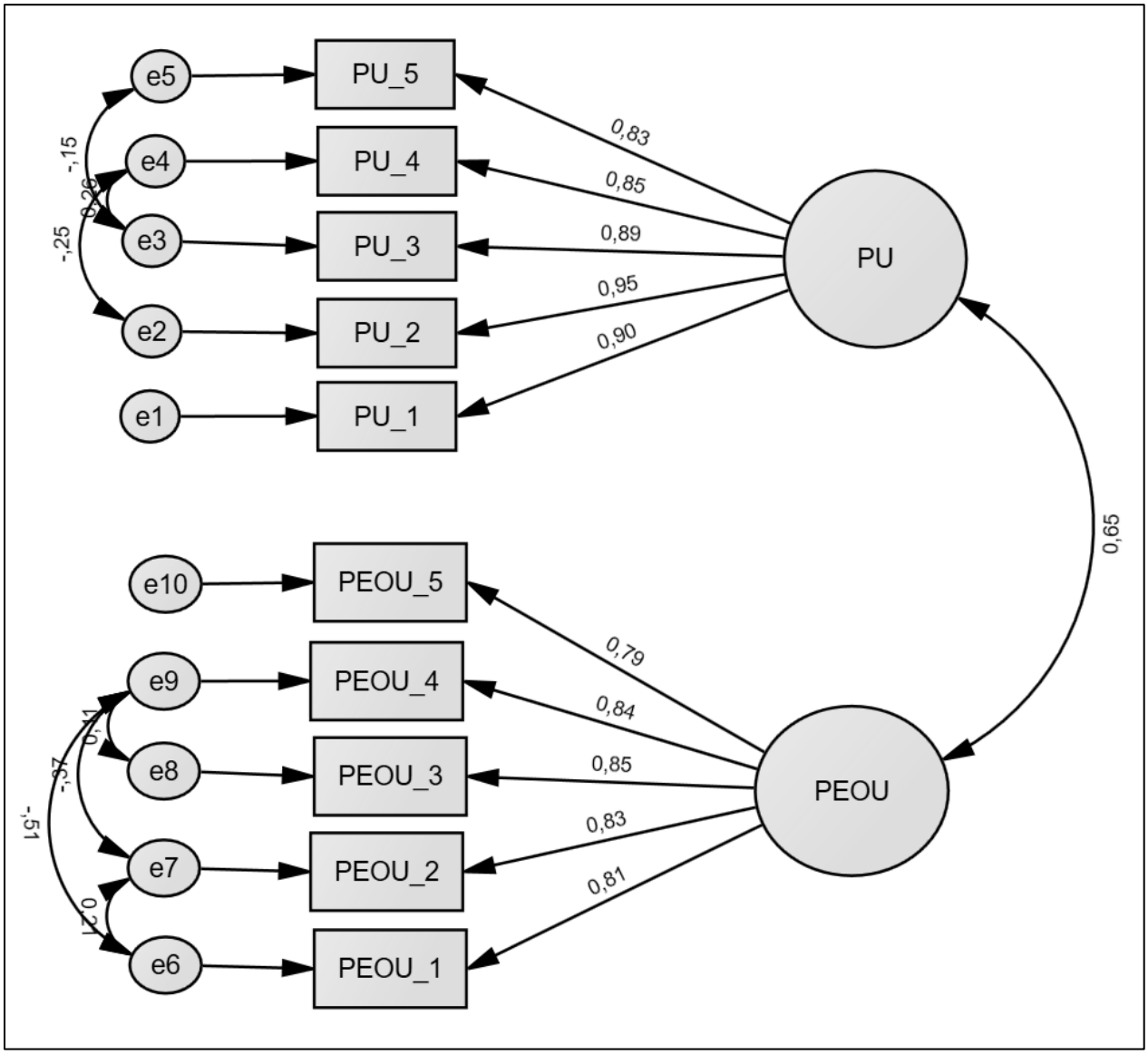
Two-Factor Measurement Model of the TAM



After considering the output from the first CFA, it was apparent that modifications to the measurement model would result in better fit. Resultantly, covariances were drawn between error terms 8 and 9, error terms 7 and 9, error terms 6 and 9, error terms 6 and 7, error terms 3 and 5, error terms 3 and 4, and error terms 2 and 3. These modifications yielded a better fit to the data than the initial model; χ^2/df = 2.26, CFI = .982, NFI = .969, IFI = .983; TLI = .971, SRMR = .039; and exhibited factor loadings ranging from λ = .79 ("My interaction with m-learning is clear and understandable") to λ = .95 ("I believe that m-learning increases my academic productivity"). The modified measurement model (along with the other λ) is depicted below.

Figure 4

Modified Two-Factor Measurement Model of the TAM



Predictive Validity

Having tested the psychometric properties of the TAM, its value in predicting m-learning usage among SwD was then explored. Using a multiple linear regression, a forced-entry method was performed where both PU and PEOU were simultaneously entered into the equation. Results from the ANOVA suggested that the model (with PU and PEOU) did not significantly predict m-learning usage among SwD (with an *F*-ratio of .049). This was corroborated by the coefficients table, which revealed non-significant betas (β) equal to .026 and -.010 (respectively), as shown below.

Table 5

Coefficients

Model		Unstandardised Coefficients		Standardised Coefficients	*t*	*Sig.*	95% Confidence Interval for *B*	
		B	Std. Error	β			Lower Bound	Upper Bound
1	(Constant)	5.393	.325		16.616	<.001	4.754	6.033
	PU	.027	.091	.026	.300	.764	-.152	.207
	PEOU	-.011	.100	-.010	-.113	.910	-.209	.186

a. Dependent Variable: m-learning usage

Discussion

Establishing Reliability Among SwD

The core constructs of the TAM exhibited excellent reliability among the sample of SwD, producing Cronbach's alpha values (and identical composite reliability coefficients) of .95 for PU and .91 for PEOU. As seen in Table 1, these results are similar to many others in the field (Davis, 1989; Rafique et al., 2020; Şahin et al., 2022; Şahin & Yıldız, 2024; Tarhini et al., 2013; Tawafak et al., 2023) or higher (Bere & Rambe, 2016; Kabir et al., 2023; Şahin et al., 2023). However, most notable (and comparable) are the findings by Şahin et al. (2022) and Şahin and Yıldız (2024), which sampled SwD and explored the acceptance of e-learning and m-learning, respectively. These findings reported Cronbach's alphas ranging between .91 (PEOU; Şahin et al., 2022) and .96 (PU; Şahin & Yıldız, 2024). Collectively, these results, together with those reported in the current study, underscore the consistency of the items measuring the core constructs in the TAM among SwD in DE settings in developing countries, regardless of the manner in which the items are adapted to fit the research context, culture, language, or disability of the participants.

Establishing Construct Validity Among SwD

In addition to establishing reliability among the sample, results from the data analysis revealed strong evidence supporting the construct validity of the TAM constructs (PU and PEOU) when contextualised to m-learning among SwD in South Africa. First, the factor loadings (λ) showed a clear distinction between PU and PEOU, with loadings ranging from .79 to .95. These factors remained unchanged from the original structure (Davis, 1989) and exhibited

loadings which are comparable to numerous studies in the field (Adams et al., 1992; Bere & Rambe, 2016; Kabir et al., 2023; Rafique et al., 2020; Šumak et al., 2011; Tarhini et al., 2013; Wong et al., 2013).

Second, the initial CFA yielded a good-fitting model (CFI = .945, TLI = .927). Post-modification, model fit improved further (χ^2/df = 2.26, CFI = .982, NFI = .969, IFI = .983; TLI = .971, SRMR = .039), validating the two-factor structure of PU and PEOU. Similar indices of fit have been reported by Rafique et al. (2020), Tarhini et al. (2013), Wong et al. (2013), and Zhou et al. (2022), all of whom explored the validity of the TAM among university students in developing countries (see Table 5 below). However, it is worth noting that these studies included additional constructs in their measurement models (e.g., attitude towards the technology, social norms, quality of work life) and sampled students without disabilities, so direct comparisons should be made with caution.

Table 6

Indices of TAM Model Fit Among Students

Study	χ^2/df	GFI	AGFI	CFI	RMSEA	SRMR	NFI	TLI
Šumak et al. (2011)	1.337	.943	.915	.984	.038	-	.939	.979
Wong et al. (2013)	2.578	.944	-	.978	.072	-	-	.967
Tarhini et al. (2013)	2.697	.909	.885	.951	.055	-	.924	-
Rafique et al. (2020)	1.307	.950	.921	.992	.025	-	.948	-
Zhou et al. (2022)	-	-	-	-	-	.073	.812	-
Current	2.258	.948	.894	.982	.076	.039	.969	.971

Establishing Predictive Validity Among SwD

Results from the multiple regression analysis revealed that neither PU nor PEOU were significant predictors of m-learning usage among the current sample of SwD (β = .026, t = .300; p = .764; β = -.010, t = -.113, p = .910; respectively). These results are in stark opposition to recent findings in the field, which have suggested that the core components of the TAM have significant paths to actual m-learning usage among university students. In the first of these studies, Drwish et al. (2023) reported that PU had a significant positive impact on actual usage (β = .133, t = 2.314; p < .001) as did PEOU (β = .123, t = 1.231; p < .001). Cumulatively, the model (which included satisfaction, information quality, system quality, service quality, PU, and PEOU) was able to account for 70.0% of the variance in m-learning usage among undergraduate and postgraduate students in Saudi Arabia. Similar results have been reported by Wu et al. (2025), who suggested that PU has a significant influence on actual m-learning *usage* among university students in China (β = .591, t = 8.049; p < .001). Considering these differences, it is essential to note that both studies (i.e., Drwish et al., 2023; Wu et al., 2025) sampled students from traditional, face-to-face universities without disabilities—nuances that cannot be overlooked and require further exploration.

Limitations and Implications

This study, like all others, is subject to limitations. First, the current study sought only to determine the reliability of the core constructs in the TAM (PU and PEOU) along with the construct and predictive validity. Future research endeavours should explore the convergent and divergent/discriminant validity of these two domains among a sample of SwD in a DE institution in South Africa. Such insights would add to the limited psychometric evidence of the TAM in the country's DE sector. Second, the focus on PU and PEOU is a notable limitation. Future studies would benefit from the exploration of other facets reportedly known to influence m-learning usage (such as satisfaction and system- and service quality; Althunibat et al., 2021; Drwish et al., 2023; Lutfi et al., 2022) or other factors known to reduce the intention-behaviour gap (such as goal dimensions or basis of intention; Conner & Norman, 2022). Third, the focus on SwD precludes any generalisations to the general DE student population. As a result, future research endeavours could explore the value of PU and PEOU in determining m-learning usage among DE students without a disability.

Conclusion

Despite these limitations, this appears to be one of the first studies to establish the psychometric properties of the core components of the TAM (PU and PEOU) and explore their predictive validity in relation to m-learning usage among SwD in a DE institution in South Africa. Overall, the results revealed favourable psychometric properties that strengthen the cultural validity of the TAM and provide additional support for its robustness among SwD pursuing their studies at a DE institution. However, given the stark results revealed in the regression analysis, which suggested that the core components inherent in the TAM are not indicative of technology usage among SwD, DE practitioners involved in inclusive practices and curriculum design should exercise caution when implementing or adopting systems based solely on their PU and PEOU. Rather, attention should be paid to the structural and disability-specific barriers in South Africa, including device and data constraints, unstable internet- and power connectivity, and imperfect integration with ATs. In parallel, the continuous refinement of platforms should be informed and co-designed with students with diverse disability profiles, ensuring that inclusive practices are grounded in actual usage rather than assumed acceptance.

Declarations

Ethics Board Approval

Ethical clearance for this study was obtained from the institution's Department of Psychology at the College of Human Sciences' Ethics Committee (Ref #: 2020-PsyREC-67141242). In addition, research permission to involve SwD was granted by the institution's Research Permission Sub-Committee (RPSC; ref #: 2020_RPSC_024).

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AI Use Statement

Generative artificial intelligence (AI) was used in the preparation of this manuscript for grammar, style refinement, and brevity using ChatGPT, Version 5.1. The AI tool was not used to generate, analyse, or interpret research data, nor to create original scholarly content. All content was reviewed, verified, and approved by the authors, who take full responsibility for the accuracy and integrity of the work.

Conflicts of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix A

Abbreviation	Item
PU_1	I believe that m-learning enhances my academic performance.
PU_2	I believe that m-learning increases my academic productivity.
PU_3	I believe that m-learning enhances my learning effectiveness.
PU_4	I believe that m-learning enhances my learning efficacy.
PU_5	I believe that m-learning is useful for my studies.
PEOU_1	Learning to use m-learning is very simple.
PEOU_2	It's easy for me to become skilful at using m-learning.
PEOU_3	I think using m-learning is easy.
PEOU_4	It is easy to use m-learning to accomplish my study tasks.
PEOU_5	My interaction with m-learning is clear and understandable.

Culturally Inclusive Practices in Online Learning: A Systematic Review of Empirical Literature

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Abstract
Online learning enrollment has grown rapidly worldwide, yet challenges persist in ensuring instruction is effective, engaging, relevant, and accessible for learners from diverse cultural backgrounds. This study systematically reviewed 72 peer-reviewed articles on culturally inclusive online learning published between 2016 and 2023. Using a systematic search, retrieval, coding, and synthesis process, the review found limited attention to underrepresented student populations and emphasized the need for community-based approaches that involve stakeholders in culturally inclusive online learning (CIOL) design and evaluation. The selected literature was informed by educational, cultural, intercultural, critical, and social justice theories, with culturally relevant pedagogy, universal design, community of inquiry, and social constructivism most frequently applied. Learning management systems were shown to support inclusion when paired with practices such as culturally responsive assessments, intercultural learning spaces, and holistic pedagogies, though application remains uneven across disciplines, particularly in STEM. Recommendations highlight expanding research on overlooked populations and advancing consistent integration of CIOL strategies across online course design elements, including objectives, materials, assessments, and interactions.

Keywords: Cultural inclusion, online learning, systematic review, culturally responsive teaching

De la Mora Velasco, E., Jardaneh, S., & Kaletski-Maisel, G. (2026). Culturally inclusive practices in online learning: A systematic review of empirical literature. *Online Learning, 30*(3), 319-352. https://do.org/10.24059/olj.v30i3.5080

Data confirms the expansion of higher education online learning, defined as "education being delivered in an online environment through the use of the internet for teaching and learning" (Singh & Thurman, 2019, p. 302). In Fall 2020, 75% of U.S. undergraduate students were enrolled in at least one online course (NCES, 2022), and by 2022, nearly 3 million students attended college fully online (Welding, 2022). Online learning encompasses various modalities, including fully online (asynchronous, web-based), mixed-mode (online and in-person), and flipped learning (pre-class online learning combined with in-person components) (Lee & Choi, 2019).

Key benefits of online include increased access (Apana, 2008), flexibility (Gillett-Swan, 2017), wider audience reach (Dumford & Miller, 2018), and cost savings for students (Nguyen, 2015). However, challenges persist, such as compensating for reduced real-time communication (Hirumi et al., 2021), increasing instructors' social presence and meaningful interactions (Keengwe et al., 2013), and providing engaging, relevant, and accessible instruction for learners from diverse cultural backgrounds (Pacansky-Brock et al., 2020).

Online courses attract diverse learners, often more so than hybrid or face-to-face modalities (Online Education Research, 2023). Online student populations are more racially diverse (ClassesandCareers, 2018), and international student enrollment increased by 80% in 2021 compared to 2020, reflecting post-COVID-19 growth (Institute of International Education, 2022). However, cultural barriers, such as language, time zones, and limited multicultural content, can hinder culturally diverse students' engagement in online learning modalities (Liu et al., 2010). Moreover, minority students often experience isolation due to one-dimensional teaching approaches and assumptions of high self-regulation (Reedy, 2019; Yeboah & Smith, 2016). Cultural differences in knowledge, communication, learning preferences, and social conduct further emphasize the need for culturally responsive online learning (Gong, et al., 2021).

This article synthesizes research to inform equitable and accessible online learning experiences. It first analyzes the concept of cultural inclusion in online learning (OL) to define the study's scope. Next, it reviews prior literature to identify efforts, gaps, and the study's purpose. The methodology section outlines research identification and analysis procedures. Findings are presented by aggregating results, followed by a discussion interpreting evidence, comparing issues with prior reviews, and critically analyzing practices aimed at enhancing cultural inclusion in online learning environments.

Culture in the Context of Online Learning

Since this paper explores cultural inclusion in online education, it is essential to examine the complexity of the concept of culture. The consideration of culture significantly impacts the design and effectiveness of online learning environments, yet it is often overlooked as a pedagogical element of online course design (Gunawardena & Jung, 2023; Kumi-Yeboah & Amponsah, 2023). Callahan (2005) cited by Kinasevych (2010) defines culture as a complex construct encapsulating shared values, group behavioral patterns, mental models, and communication styles, which is crucial for online learning interactions. Cultural considerations should be integral to developing these environments to ensure meaningful interactions between learners and instructors.

Culture influences learners' perceptions and interactions with other learners, the content, and online tools. Kinasevych's (2010) research highlights that online learning environments are not culturally neutral; they are shaped by the cultural backgrounds of both designers and users. The importance of culture is evident as learners approach online

environments with their own cultural perspectives and expectations. Therefore, understanding and integrating cultural dimensions into the design of online learning environments can enhance learner satisfaction and academic success.

Cultural Inclusion in Online Learning

Cultural inclusion has been defined in multiple ways. The literature suggests a lack of consensus in the definition of cultural inclusion by interchangeably using cultural inclusion (Marrone, 2013), cultural inclusivity (Dreamson et al., 2016), cultural responsiveness (Ballenger & Jiang, 2021; De la Mora Velasco et al., 2026), and cultural sensitivity (Foronda, 2008). For example, cultural inclusion is considered a collection of shared perceptions of the world and our place in it that persists by way of interaction (Frechette et al., 2019). Similarly, inclusion in the context of online learning fosters a sense of belonging to a community, and feeling appreciated for one's unique characteristics, perspectives, contributions, and ways of thinking (Gunawardena, 2020).

In the context of cultural diversity in online learning, it is important to understand learning as referring to a multifaceted process influenced by cognitive, social, and motivational factors unique to each cultural group (Illeris, 2018). Pedagogy involves the implementation of inclusive teaching practices, integration of technology, and curriculum design that respects and reflects cultural diversity (Tapanes et al., 2009). For cultural inclusivity to occur, pedagogy in online learning should be flexible, adaptable, and meaningful to students from various cultural and language backgrounds (Gurjar & Bai, 2023). Similarly, teaching an inclusive online course involves recognizing people historically excluded from educational opportunities and underscoring the development of certain skills and knowledge to incorporate effective practices into the curriculum (Milheim, 2015). In sum, inclusive online teaching reaches beyond nationality and ethnicity to also include cultural attributes such as ability, language, age, lifestyle, and other "sub" cultural differences (Marrone et al., 2013).

The above-cited definitions lay the foundation for the importance of online learning design that incorporates differing perspectives and cultural norms as well as online delivery that is flexible, engaging, and adaptable. However, the panoply of definitions may obfuscate the understanding and application of the term. Therefore, for comparative reasons and to facilitate the analysis of the existing literature, we use the definition posited by (Gay, 2018) referred to as the pedagogy that focuses on understanding the cultural backgrounds of students in online environments, acknowledging students' differences, and applying teaching strategies and materials that are culturally relevant. This definition was selected for its comprehensive integration of cultural responsiveness with practical pedagogical strategies, providing a robust framework that bridges theoretical understanding with classroom application.

Prior Reviews on Cultural Inclusion in Online Learning

Uzuner (2009) reviewed twenty-seven studies on asynchronous learning networks to understand the cultural influences on online learning, highlighting that international students were less critical online than their American peers and calling for future research to explore domestic diversity cultures and avoid homogenizing learners. Marrone et al. (2013) examined four MOOC platforms through Universal Instructional Design principles, finding that adaptability, intercultural dialogue, and contextual support are vital for cultural inclusion. Similarly, Dreamson et al. (2017, 2018) emphasized the need for individual-focused pedagogies and the need to identify LMSs (define LMS) as sociocultural spaces impacting academic success. Kumi-Yeboah et al. (2020) identified barriers to integrating cultural diversity in online teaching, including the absence of clear definitions and insufficient support

for instructors. In consonance, Yamo et al. (2022) proposed a framework for cultural engagement, highlighting community relationships and representation in communications as critical for fostering cultural inclusion.

Although prior reviews have advanced understanding, they have limitations. Most focus on Asian learners rather than local cultural diversity, and distinctions between cultural and individual learning preferences are often unclear. Additionally, the COVID-19 pandemic has magnified issues of inclusion, creating both challenges and opportunities. Students in low-income and rural areas faced challenges due to a lack of access to necessary technology and reliable internet connectivity. Additionally, students with accessibility needs often found courses that had shifted to remote learning did not have the needed tools to facilitate their learning. In many cases the sudden shift to emergency remote learning revealed gaps in teacher training and preparedness, and teachers struggled to engage students from diverse backgrounds in virtual settings (Akpen et al., 2024). Additionally, there is a lack of synthesized, research-based practices for stakeholders to inform the design of inclusive online courses. Addressing these gaps, this review systematically analyzes key literature to identify theoretical underpinnings, methodologies, and actionable guidelines for advancing culturally inclusive online learning.

Purpose and Research Questions

The purpose of the present study is to systematically review empirical research on Culturally Inclusive Online Learning (hereinafter referred to as CIOL). The CIOL abbreviation was developed by the authors to address the lack of a comprehensive term that encapsulates the concept of cultural diversity in online learning environments. By introducing CIOL, the authors aim to provide a unified framework that highlights the importance of culturally inclusive online education. The research questions that guided the present study are listed as follows:

1. What are the theoretical underpinnings of the research on CIOL?
2. What instructional technologies have been applied and what are their outcomes?
3. How have learning theories and frameworks informed technological implementations in the CIOL context?
4. What research-based practices for CIOL have been proposed in the OL literature?

Method

Search and Inclusion/Exclusion Criteria

We used Cooper's (2015) systematic approach to standardize and make explicit the search and analysis methods, to ensure all relevant literature was included, and to reduce potential biases in accounts of research. Cooper's framework outlines key stages of research synthesis, including problem formulation, literature search, data evaluation, data analysis and interpretation, and presentation of results. By following this structured process, we sought to ensure methodological rigor and transparency in our review. First, the research team along with a subject matter librarian discussed the research questions and the purpose of the study. The Boolean search (*online learning* or *e-learning* or *distance learning* AND *inclus**) was used to search within articles' subject terms. The terms *online learning, e-learning*, and *distance learning* were employed in the Boolean search to ensure a broad capture of relevant literature. Although it is acknowledged that these terms are often used interchangeably, they possess distinct nuances (Moore et al., 2011). Nevertheless, recognizing that some articles or

authors may use these terms variably in their research, all three were included to ensure comprehensive coverage in the literature review.

A subject matter librarian and the coauthors selected four databases to search the key terms: (1) *EBSCOhost Education Source*, (2) *Applied Science & Technology Source*, (3) *Education Resources Information Center (ERIC),* and (4) *Library Literature & Information Science Full Text (H.W. Wilson*). These four were selected because they focus on indexing major journals in the field of education. This strategy increased the likelihood that the search would yield a comprehensive set of relevant research that meets the search criteria while minimizing the inclusion of irrelevant results.

Research published in English between 2016 and 2023 in scholarly, peer-reviewed, and full-text journals was included. The decision to include articles published between 2016 and 2023 is supported by the exponential growth in OL that began around this period. After 2016, OL platforms such as Coursera saw significant increases in user enrollment, reflecting a growing global shift towards digital education (World Economic Forum, 2021). This expansion was further accelerated by technological advancements and increased access to internet-based learning (O'Bryan, 2018), making this period critical for capturing relevant research on cultural inclusion in OL environments.

Articles were included if they explicitly addressed cultural inclusion, provided empirical or theoretical insights into OL practices, and aligned with the study's research questions. Conference proceedings and dissertations were excluded to ensure the selected articles were checked by academic peers in terms of validity, suitability for publication, and methodological soundness. Articles were excluded if they lacked a clear focus on cultural inclusion, presented insufficient data or analysis, or primarily discussed general aspects of online learning without addressing cultural contexts. No limitations were placed on the locality of the research, and search results yielded studies produced from several different countries across the globe. This decision allows the authors to get a broader perspective of the research questions on a global scale, rather than limiting results to the cultural inclusivity practices in one country or region.

Screening of Articles

The search yielded 123 records that were integrated into an electronic dataset for initial screening. Two of the coauthors manually screened the titles and abstracts of the retrieved research to confirm that the articles were centered on aspects of cultural inclusion (e.g., ethnicity, race) and online learning (e.g., contents, activities, assessments). After the initial screening, 63 articles were excluded for duplication, a central focus on the inclusion of students with disabilities or special needs, a K-12 setting, a focus on COVID-19 emergency remote teaching, a focus on non-academic aspects of distance education (e.g., immigration services), or foreign language learning as the outcome. Seventy-two articles were included in the review and were further examined through manual coding.

Coding

The three coauthors coded the totality of the articles by conducting full-text screening, selecting coding categories to fit the research questions. The *a priori* codes were defined by the research team to address the research questions and then extracted from the selected articles. The codes included type of article, subject matter, learning modality, theoretical or conceptual underpinning, key outcome, sample or audience, sample size, key finding or proposition, course component, technology used, and challenges reported by the participants

included in the selected study. Each coauthor independently coded a subset of the articles, after which the team convened to compare coding results, resolve discrepancies, and reach a consensus on how the codes represented the data. Through this iterative and collaborative process, the codes were analyzed for patterns, grouped into broader categories, and synthesized to address the research questions. The coding dataset was also used to filter, sort, and represent the data to highlight trends and relationships across the coded data, ensuring that the categories presented were grounded in the systematic analysis of the articles.

Limitations

To minimize bias, we followed Cooper's (2015) systematic approach, applying explicit criteria and independent screening procedures to guide study selection and coding. Nonetheless, some limitations should be noted. Restricting searches to a few databases and English-only publications may have excluded relevant non-English and gray literature, and time-frame limits may have omitted older yet valuable studies. In addition, we did not conduct a formal appraisal of article quality. This decision was based on both the limited number of available studies and the lack of a single, standardized instrument for assessing quality across the diverse research designs included in CIOL scholarship. Future reviews could address this gap by applying design-specific appraisal tools or by developing criteria tailored for multidisciplinary evidence.

Results

Descriptive Findings

Seventy-two articles on CIOL were selected for this review; publications averaged 9 per year between 2016 and June 2023. Research output decreased from 2016 to 2018, peaked in 2021, and declined thereafter (Figure 1). Nearly half of the studies were conducted in the U.S. (n = 35), with smaller contributions from Australia (n = 5) and Canada (n = 4), while the rest were distributed globally. The primary publication outlets were *Online Learning* (n = 5), *Australian Journal of Educational Technology* (n = 3), and *Journal of Teaching and Learning with Technology* (n = 3) (Figure 2).

Figure 1

Number of articles published on cultural inclusion and online learning between 2016 and 2023.

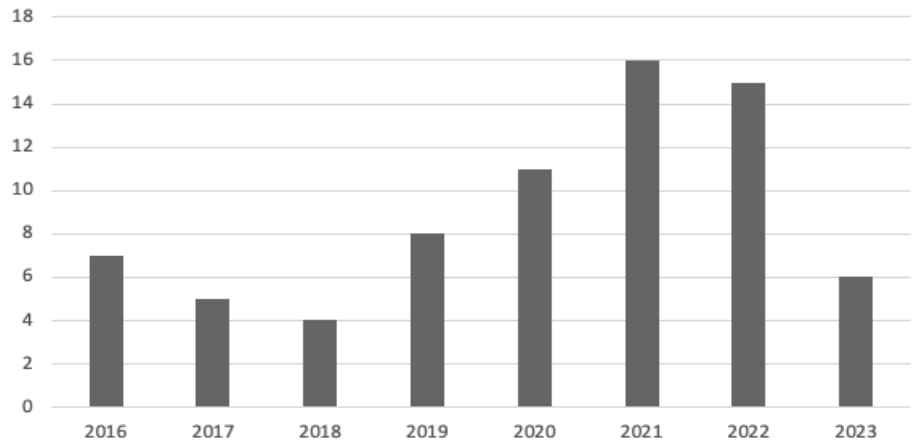
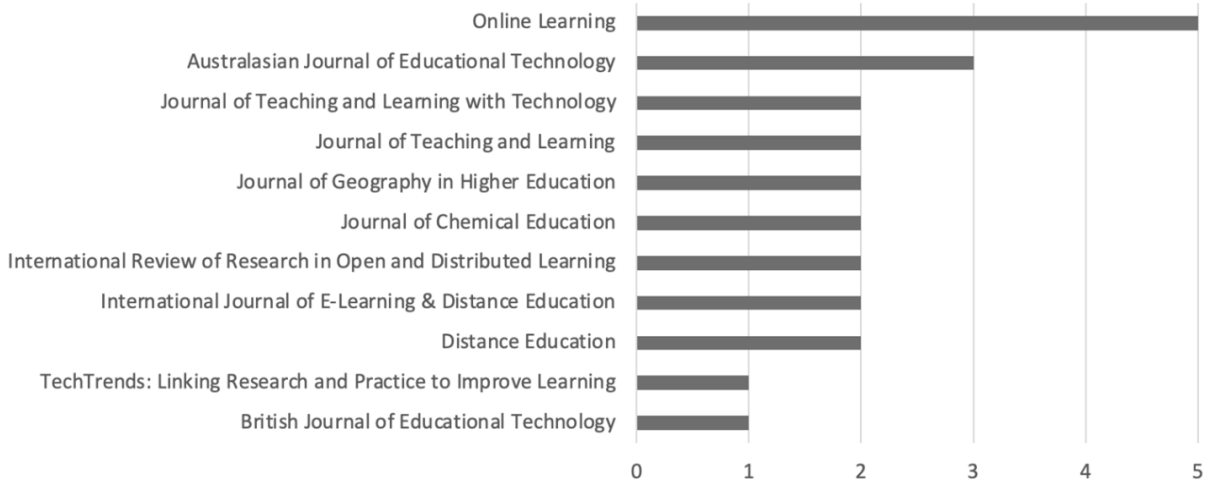


Figure 2

Main Journals That Publish Research on Cultural Inclusion and Online Learning



The selected literature employed diverse terminology to describe the student populations studied. Figure 3 visualizes audience terms, with “international”" and “diverse” appearing most frequently in abstracts. Some studies focused on specific populations, such as indigenous, Chinese, military, or first-generation students. Others used broader terms like “intercultural,” “global,” “multicultural,” and “"marginalized.” These findings indicate that underrepresented student populations have not been equally explored.

Figure 3

Word Cloud of Audience Examined in the Selected Articles



The selected articles include empirical qualitative studies (e.g., analysis of syllabi, forums, interviews, thematic reviews), and quantitative research (e.g., surveys, group comparisons). Nearly a quarter of the studies used mixed methods (e.g., design-based studies), conceptual approaches (e.g., essays), theoretical frameworks, or case studies. This

diversity in epistemological and methodological approaches provides a comprehensive view of CIOL research. However, the findings highlight the need for community-based approaches that actively involve educational stakeholders in designing, implementing, and evaluating CIOL programs, practices, policies, and processes. Regarding methodology, of the 72 articles reviewed, 28% were qualitative (n = 20), 25% research syntheses (n = 18), 12% surveys (n = 9), 12% quantitative (n = 9), 8% mixed methods (n = 6), and 6% each for case studies (n = 4), conceptual papers (n = 4), and theoretical papers (n = 4).

Quality Appraisal

To evaluate the methodological and educational quality of the studies included in this review, we conducted a structured quality appraisal using the framework proposed by Gordon and colleagues (2011, 2020). This framework was specifically developed for assessing educational interventions and emphasizes dimensions that extend beyond methodological rigor to include pedagogical and contextual depth. The appraisal criteria included six key components: (1) theoretical underpinning, referring to the extent to which the study is grounded in established learning or instructional theories; (2) curriculum or syllabus design, assessing the clarity, coherence, and alignment of learning objectives, activities, and assessments; (3) setting, which captures the educational context and learner characteristics relevant to interpreting outcomes; (4) pedagogy, evaluating the appropriateness and articulation of instructional approaches; (5) content, assessing the accuracy, relevance, and suitability of instructional materials; and (6) strength of conclusion, which considers whether the conclusions are logically derived and adequately supported by empirical or theoretical evidence. Each study was assessed simultaneously by the three coauthors using a 3-point scale (0 = absent, 1 = partial, 2 = clear/strong), and discrepancies were resolved through discussion to ensure reliability.

The 72 selected studies were appraised using Gordon et al.'s (2011, 2020) six quality criteria (see Table 1). Most studies demonstrated strong theoretical grounding, often drawing on frameworks such as constructivism, transformative learning, Universal Design for Learning (UDL), culturally responsive pedagogy, and community of practice. Curricular and pedagogical alignment were also well articulated, with many studies linking learning objectives, activities, and assessments. A clear trend emerged toward integrating diversity, equity, inclusion, and intercultural competence within educational design, emphasizing human-centered and inclusive approaches. Although most studies described detailed settings and relevant content, fewer included measurable outcomes, relying instead on qualitative evidence. Overall, the findings suggest a mature, theory-informed body of work focused on inclusivity and contextual relevance, yet still developing in terms of empirical rigor and long-term impact assessment.

Table 1

Results of Quality Appraisal

Author(s) (year)	Theoretical Underpinning	Curriculum or Syllabus Design	Setting (Educational Context & Learner Characteristics)	Pedagogy	Content Quality	Strength of Conclusion	Total

Abramenka -Lachheb 2022	2	2	2	2	2	1	11
Al-Azawei et al. (2016)	2	1	1	1	2	1	8
Al Hashlamoun (2021)	2	1	1	1	2	1	8
Araujo Dawson et al. (2022)	2	1	2	2	2	1	10
Ballenger & Jiang (2023)	2	1	2	1	2	1	9
Brooks et al. (2021)	2	1	2	2	2	1	10
Castrillo & Sedano (2021)	2	2	2	2	2	2	12
Chang & Benson (2022)	1	1	2	2	2	1	9
Chen et al. (2020)	2	1	1	2	2	0	8
Cochrane & Maposa (2018)	2	1	2	2	2	1	10
Collier & Ross (2017)	2	0	1	1	2	0	6
Dreamson (2017)	2	1	1	2	2	1	9
Dreamson (2018)	2	1	1	2	2	1	9
Dube (2020)	2	1	2	2	2	2	11
Dunn (2021)	2	1	2	2	2	2	11
Eppard & Rudd (2021)	2	2	2	2	2	2	12
Fermín-González (2019)	2	2	2	2	2	2	12
Finkelstein et al. (2022)	2	2	1	2	2	1	10
Foltz & Brown (2022)	2	1	2	2	2	1	10
Gourlay et al. (2021)	2	1	2	2	2	2	11
Green (2017)	2	1	2	2	2	1	10
Gronseth (2018)	2	2	2	2	2	2	12
Gunawardena et al. (2020)	2	2	2	2	2	2	12
Guo-Brennan (2022)	2	2	2	2	2	2	12
Heitner & Jennings (2016)	2	1	1	2	2	1	9
Hunt & Oyarzun (2020)	2	1	2	2	2	1	10
Hutchins & Goldstein Hode (2021)	2	2	2	2	2	2	12
Jabbar & Mirza (2017)	2	1	2	2	2	2	11
Kang & Han (2016)	2	1	2	2	2	1	10
Kanwar et al. (2020)	2	2	2	2	2	2	12
Kerr & Merciai (2015)	2	1	2	2	2	2	11
Khoo et al. (2022)	2	2	2	2	2	2	12
Knauf (2016)	1	1	2	2	2	1	9
Koponen (2019)	2	1	1	2	2	1	9
Kumi-Yeboah et al. (2016)	2	2	2	2	2	2	12
Lambert (2019)	2	2	2	2	2	2	12

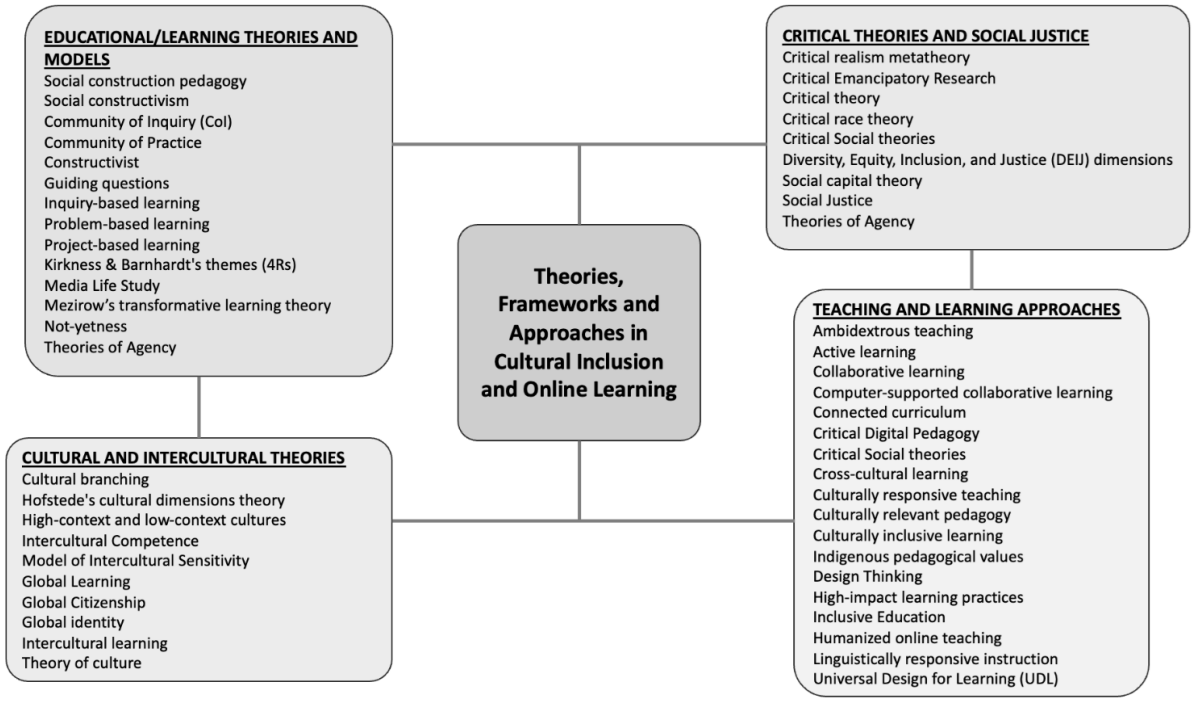
Lee & Bligh (2019)	2	2	2	2	2	2	12
Lowenthal et al. (2020)	2	2	2	2	2	2	12
Manna & Mennicke (2022)	2	2	2	2	2	1	11
Mays (2016)	2	1	2	1	2	1	9
McCarron & Yamanaka (2022)	2	1	1	2	2	1	9
McLaughlan (2021)	2	1	2	2	2	1	10
McLaughlan (2023)	2	1	2	1	2	2	10
Morong & DesBiens (2016)	2	2	1	2	2	1	10
Munger et al. (2023)	2	2	2	2	2	2	12
Herrera-Nieves et al. (2019)	2	2	2	2	2	1	11
Nkomo & Daniel (2021)	2	1	2	1	2	2	10
Ortiz-Rodríguez et al. (2022)	2	2	2	2	2	2	12
Osei-Tutu et al. (2021)	2	2	2	2	2	2	12
Pacansky-Brock et al. (2020)	2	2	2	2	2	2	12
Reedy et al. (2019)	2	1	2	2	2	1	10
Reid et al. (2021)	2	2	2	2	2	2	12
Ricardo-Barreto et al. (2022)	2	2	2	2	2	2	12
Sadykova & Meskill (2019)	2	2	2	2	2	2	12
Salvo et al. (2019)	2	1	2	2	2	2	11
Schieble & Pollcek (2021)	2	2	2	2	2	2	12
Schirmer & Lockman (2022)	2	2	2	2	2	2	12
Siergiejczyk (2020)	2	2	2	2	2	2	12
Soroka (2022)	2	1	2	2	2	1	10
Sousa et al. (2021)	2	2	2	2	2	2	12
Steyn et al. (2021)	2	2	2	2	2	1	11
Sunasee (2023)	2	2	2	2	2	2	12
Thomas et al. (2021)	2	1	2	2	2	1	10
Torras et al. (2017)	2	2	2	2	2	2	12
Vail (2018)	1	1	2	1	2	1	8
Valcarlos et al. (2020)	2	2	2	2	2	2	12
Van Houweling (2021)	2	2	2	2	2	2	12
Wilks et al. (2020)	2	2	2	2	2	1	11
Winstead et al. (2022)	2	2	2	2	2	2	12
Yeboah et al. (2023)	2	2	2	2	2	2	12
Yesmin et al. (2021)	2	2	2	2	2	1	11
Zhu et al. (2022)	2	2	2	2	2	2	12

Results of RQ1

It was found that CIOL research has been informed by existing theories, models, and frameworks that can be categorized into educational, cultural, and intercultural, critical, social justice, and teaching approaches (Figure 4). In our categorization of theories, models, and frameworks, the boundaries of each theoretical category were determined by examining the primary focus and objectives of the theories in relation to their application in online learning. Educational theories primarily emphasize learning processes, instructional design, and pedagogy, while teaching theories focus on specific methodologies for delivering content. Critical and social justice theories are distinguished by their focus on challenging power structures, promoting equity, and addressing systemic inequalities in educational environments. Cultural and intercultural theories, on the other hand, center on the impact of cultural contexts, cross-cultural communication, and the inclusion of diverse perspectives in learning experiences. Each category was defined by the theoretical underpinnings that guided the study's design, objectives, and intended outcomes.

Figure 4

Theoretical Underpinnings of Literature in Cultural Inclusion and Online Learning



Of note, the culturally relevant pedagogy theory (Ladson-Billings, 1995), universal design (UDL) (Rose & Meyer, 2002), community of inquiry (Garrison, Anderson and Archer, 2000), and social constructivism (Vygotsky, 1978) were the most recurrent in the CIOL literature. Culturally responsive pedagogy was probably predominant because it supports online learners' awareness, community building, cognitive development, and critical consciousness to make the curriculum equitable and inclusive. Constructivism, community of inquiry (CoI), and social constructivism were also noted in the literature because of the focus on student-led practices in assignments and activities and active, collaborative, high-impact, humanized teaching, and learning. Critical theories based on social justice, such critical race theory and theories of agency were found. Cultural and intercultural theories, such as cultural

branching, module of intercultural sensitivity, and global identity emphasize high critical thinking expectations for all students, connecting real-world issues to students' lives, and providing historical and multiple perspectives of societal inequities against marginalized groups (Kayser & Starks, 2021).

A multiplicity of theories informed the selected CIOL research. Researchers frequently employed theories of different traditions, ranging from educational and intercultural to critical and teacher-oriented. However, the high number of theories utilized may also complicate the advancement of this research area, as it introduces a wide range of variables and measurement instruments, leading to inconsistencies and challenges when measuring the impacts of interventions and their related outcomes.

Results of RQ2

Table 2 highlights the main technologies used in CIOL literature. The analysis of recent literature on CIOL highlights a clear emphasis on leveraging Learning Management Systems (LMS) as the most recurrent technology, often coupled with discussion forums and videoconferencing tools. The studies demonstrate that LMSs are instrumental in promoting inclusivity through thoughtful pedagogical practices such as culturally responsive assessments, intercultural learning spaces, and holistic pedagogies. However, there is a notable challenge, particularly in STEM fields, that culturally inclusive strategies may not yet be universally applicable or effectively implemented across all disciplines.

Additionally, Massive Open Online Courses (MOOCs), virtual exchanges, and social media (e.g., Instagram) show promising trends for enhancing inclusivity by facilitating international and intercultural connections, particularly benefiting migrants, refugees, and geographically diverse students. Despite these advancements, critical issues persist; mobile-based learning, for instance, has exposed a digital divide experienced by rural learners (Wahyuni et al., 2024). Thus, while technology broadens opportunities for inclusivity, its effectiveness remains contingent upon equitable access, sustained instructor engagement, and culturally relevant pedagogical frameworks.

Table 2

Articles That Reported Uses of Technologies in Cultural Inclusion and Online Learning and Key Findings

First Author	Year	Strategy/ technology	Key Finding
Knauf	2016	Audio	Students are open and positive about audio feedback and perceived it as more personal.
Finkelstein	2022	Cloud-learning solutions and Videoconferencing	A multidimensional model of Culturally Relevant Academic Evaluation (CRAE)
Guo-Brennan	2022	CMS, discussion forums, blogs, email, web-conferencing, chats, and videoconferencing.	Virtual environments and available digital tools offer new possibilities to enhance equity and inclusion in higher education.
Eppard	2021	Collaborative online document	Educational technology helps establish dialogue between instructors/students
Zhu	2022	Instagram	Instagram-Based Inclusive Online Learning Community helps embrace demographic and location Diversity.
Araujo Dawson,	2022	Laptops available for students	Equity-minded approach can strategically address the academic, social, and cultural integration of racialized people.
Sadykova,	2019	LMS	Thoughtful accommodations and online language socialization can lead to positive learning experiences.
Dreamson	2018	LMS	Indigenous students expect to experience more human-to-human interactions and develop a sense of community.
Abramenka-Lachheb	2022	LMS	Guidelines and examples are provided to implement Authentic Assessments Designed Through the DEIJ lenses.
Reedy	2019	LMS	Identified 10 themes and 6 principles for course design
Dreamson,	2017	LMS	Indigenous holistic pedagogies have a metaphysical strength to be the ontological foundation for cultural inclusivity.
Torras	2017	LMS	Awareness of cultural differences and willingness to integrate participants from other cultures facilitate intercultural learning spaces.

Kumi-Yeboah	2023	LMS	Instructors used culturally responsive pedagogy by integrating multicultural content and cross-cultural activities; challenges existed in STEM fields to adopt culturally inclusive strategies.
Winstead	2022	LMS and 3D simulations	Community engagement (addressing health disparities) helps create more culturally relevant online courses.
Schirmer	2022	LMS and discussion forums	Discussion prompts could be written to culturally incorporate responsiveness in online learning.
Vail	2018	LMS, discussion forums, videos, social media, cell phones	Incorporating digital learning requires more dynamic, and culturally responsive pedagogy
Koponen	2020	LMS, online collaborative tools, social networks	Media Life Study is reflexive pedagogical method brings opportunities and awareness of the transcultural society.
Thomas	2021	LMS, Videoconferencing	Module evaluation becomes an ongoing process in which alterations are made in real-time and to subsequent learning encounters with students.
Dube	2020	Mobile App	Online learning excludes rural learners due to a lack of resources.
Castrillo	2021	MOOC	MOOCs help migrants/refugees to integrate in their new communities.
Siergiejczyk	2020	MOOC	International exchange provides tool for equitable, diverse classrooms.
Kerr	2016	MOOC	There are three drivers of diversity in online learning: approach, language, and personalization.
Brooks	2021	MOOC	Learner's region impacts propensity to open emails.
Nieves	2019	MOOC	ADDIE and UDL can inform the creation of MOOCs o
Jabbar	2019	MOOCs, portfolios	Additional emphasis needs to be placed on developing a practical and functional approach which embeds cultural branching via technological platforms.
McCarron	2022	Narrative video, posting of video and audio, discussion boards, OER, Video-based	Addressing cognitive, social, teaching, and learner presence in the pursuit of culturally relevant/sustaining and equitable online leadership education is fundamental.

		role play, virtual experiential learning, synchronous backchannel discussion.	
Collier	2017	OERs	Pedagogies such as federated wikis and agents beyond the course can engage with boundary-crossings between openness and closure and demonstrate the value of perspectives that such engagements bring to the fore.
Foltz	2022	Videocasting and discussion boards.	Incorporating interpersonal connections as part of the course design, community-focused courses, considering how time zones, faculty empathy.
Sunasee	2023	Video discussions	Weekly DEI activities and assessments enhanced student awareness of DEI in STEM and promoted an inclusive environment.
Ortiz-Rodríguez	2022	Videoconferencing	Virtual Co-classes offered concurrently with academic courses can be used to provide inclusive environment and reduce equity gaps for underrepresented students to succeed academically and provide them skills.
McLaughlan	2023	Videoconferencing	Students feel preference for social engagement in F2F compared to OL.
Chang	2022	Virtual classrooms	Jigsaw-based case discussion integrating cloud-based collaboration enable to connect with students from different cultures in class.
Schieble	2021	Virtual field experiences	Virtual field experiences depend on strength of pedagogy.
Munger	2023	Virtual exchange (videoconferencing and LMS)	Virtual exchange activities facilitated intercultural communication and awareness, leading to stronger culturally inclusive experiences in online learning.
Mann	2022	Virtual platform	Students and faculty engaged virtually in real time, using the physical environments in each location can enhance collaboration and active learning.

Results of RQ3

Analysis of the 72 appraised studies revealed relationships between theoretical frameworks and the technologies employed. Table 3 shows the relationships between key focus areas, theories or frameworks, and associated technologies. The dominant learning paradigms were constructivist, transformative, and social learning theories, which guided the

use of collaborative and reflective technologies that positioned learners as active participants in meaning-making (Kumi-Yeboah et al., 2017; Kang & Han, 2016; Zhu et al., 2022). Instructional design frameworks such as Universal Design for Learning (UDL) and the Community of Inquiry (CoI) framework were prevalent, particularly in studies leveraging LMS-integrated tools and adaptive feedback mechanisms to enhance accessibility and social presence (Gronseth, 2018; Lowenthal et al., 2020; Reedy et al., 2019)

Table 3

Theoretical Frameworks and Related Technologies Across the 72 Appraised Studies

Focus Area	Dominant theories and frameworks	Associated Technologies
Learning Theories	Constructivism, Social Constructivism, Transformative Learning, Connectivism	Learning Management Systems (Canvas, Moodle), collaborative tools (Zoom, Microsoft Teams, Google Docs), and discussion boards supporting reflection and peer interaction
Instructional Design Frameworks	Universal Design for Learning (UDL), Community of Inquiry (CoI), Design-Based Research (DBR)	LMS-integrated accessibility tools, adaptive course shells, online rubrics, and embedded analytics for engagement and feedback
Critical & Intercultural Perspectives	Culturally Responsive Pedagogy, Critical Pedagogy, Critical Race Theory, Global Citizenship Education	COIL platforms, virtual exchanges, multilingual course sites, and reflective e-portfolios for intercultural dialogue
Student-centered approaches	Authentic Learning, Experiential Learning, Situated Learning	MOOCs, virtual simulations, immersive role-play tools, and digital storytelling platforms (e.g., VoiceThread, Flipgrid)
Emerging topics	Humanizing Pedagogy, Socio-emotional Learning, Inclusive Digital Design	Video-based learning (Panopto, YouTube), AI feedback systems, AR/VR simulations, and social media (Padlet, Instagram, X)

.

The integration of critical and intercultural perspectives (Abramenka-Lachheb & Lachheb, 2022; Houweling, 2021; Osei-Tutu et al., 2021; Lambert, 2019) was evident in the widespread use of CIOL environments, virtual exchanges, and multilingual course interfaces, all designed to foster equity, diversity, and global collaboration. Technologies supporting authentic and experiential learning, including MOOCs, simulations, and digital storytelling, reflected situated learning principles by emphasizing application and contextual problem-solving guided by the student-centered paradigm (Gunawardena et al., 2020; Cochrane & Maposa, 2018; Thomas et al., 2021). Finally, a newer category of studies incorporated emerging and humanizing technologies, such as AI-enabled feedback, social media for

reflective interaction, and video-based learning for affective connection (Sunasee, 2023; Winstead et al., 2022; Yeboah et al., 2023).

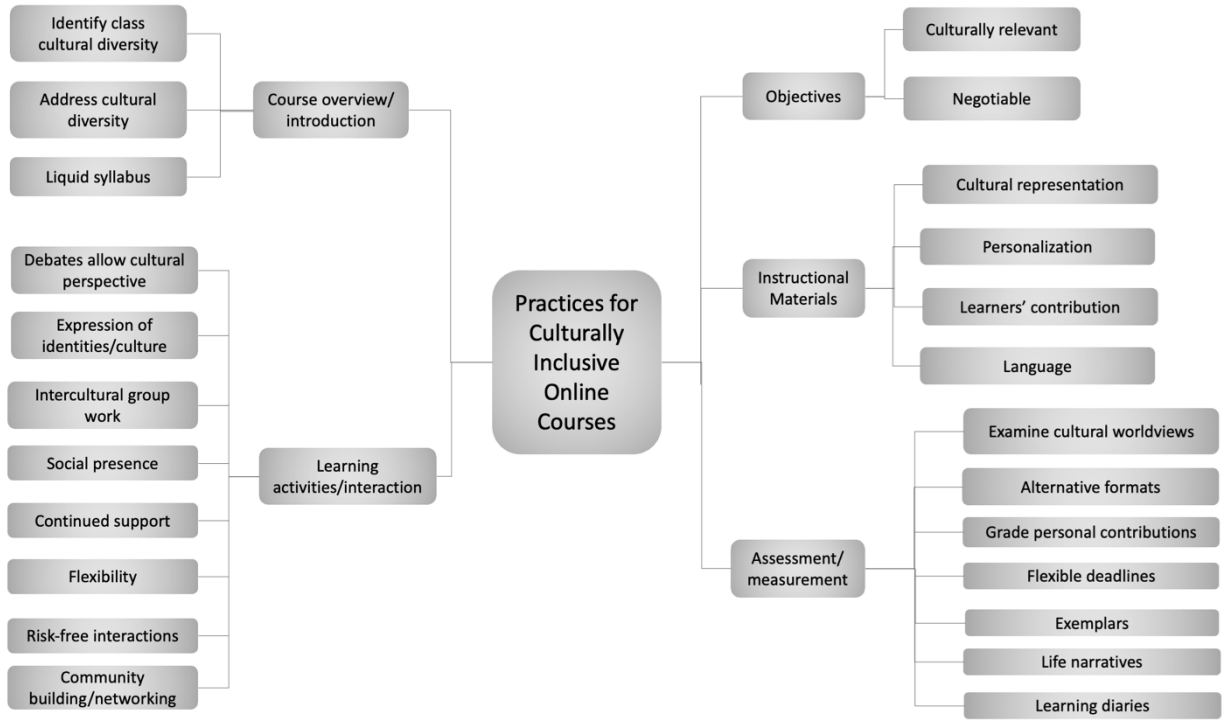
Together, these findings indicate a clear trend toward integrating theoretical frameworks with digital tools that support participation, reflection, and personalization. The most effective designs were those that aligned technology affordances with pedagogical intent, reinforcing Gordon et al.'s (2011, 2020) emphasis on theory-informed, contextually grounded educational practice (Hirumi et al., 2021.

Results of RQ4

The selected research distilled numerous practices to enhance cultural inclusion in online courses. Figure 6 and Figure 7 encapsulate the reported CIOL practices. To facilitate its practical application, the reported practices (Quality Matters, 2023) are organized based on key aspects of online courses: course overview and introduction, learning objectives, instructional materials, assessments, and measurement, and learning activities and interactions, which are first explicated in Figure 6. Then, course technology, both as a conduit for inclusion (e.g., enabling access and communication, and assistive tools) or as an integrated element in a course design component (e.g., virtual field experience, video discussion) are depicted in Figure 7 and explained further.

Figure 6

CIOL Practices for Objectives, Instructional Materials, Assessments, Course Overview and Introduction, and Learning Activities/Interactions.



Course Overview and Introduction

Multiple practices have been applied to enhance cultural inclusion in course introductions. Pre-course communication helps accommodate students from diverse locations (Foltz & Brown, 2022). A positive virtual presence with warm greetings fosters belonging for

culturally diverse students (Sousa, 2021). Similarly, discussing access to materials and submissions expectations benefit students from various backgrounds (Chen et al., 2020). Surveys can help to identify students' preferred communication methods, barriers to success (Pacansky-Brock et al., 2020) and cultural heritage (Abramenka-Lachheb & de Siqueira, 2022; Kumi-Yeboah et al., 2017). Strategies to humanize online learning include fostering empathy and creating judgment-free environments (Pacansky-Brock et al., 2020). A "Module 0" can connect content to cultural experiences, reducing alienation (McCarron & Yamanaka, 2022), while liquid syllabi enhance social presence and encourages collaborative course guidelines (Dawson, 2022; Pacansky-Brock et al., 2020). Instructors can set the tone by including a welcome message that acknowledges cultural diversity, encourages participation from all backgrounds, and affirms inclusion as a course value (Kumi-Yeboah et al., 2018).

Course Objectives

Course objectives should be meaningful to learners from diverse backgrounds and tailored to varying interests and motivation levels (Dawson, 2022: Lowenthal et al. 2020; Kang & Chang, 2016). Learning objectives should include cultural perspectives or competencies to signal the value of diversity and global understanding in the course outcomes (Sunasee, 2023). Our findings also suggest that allowing learners to negotiate and define personally relevant learning goals within their cultural contexts enhance inclusivity and engagement (Dawson, 2022: Morong & Desbiens, 2016).

Instructional Materials

Guo-Brennan (2022) highlights the importance of instructional materials with diverse cultural perspectives to create inclusive curriculum. McCarron and Yamanaka (2022) suggest involving guest contributors to enrich students' understanding of their culture and lived experiences, while also ensuring course materials, such as texts, videos, and assignments, reflect students' diverse backgrounds. Dawson (2022) emphasizes the value of including underrepresented scholarly works, addressing diversity throughout the course, and using ethnically diverse visuals in course materials. Similarly, Cochrane and Maposa (2018) recommend selecting culturally relevant learning tools, such as case studies from various cultural contexts. Reedy (2019) further advocates for incorporating indigenous and diverse perspectives in learning materials to recognize and value the richness of varied cultural viewpoints. Additionally, Sunasee (2023) suggests including readings, videos, and case studies that represent scholars and practitioners from various cultural and racial backgrounds to reflect the diversity of the student body. These practices collectively enhance the inclusivity and breadth of academic discourse.

Learning Activities and Interactions

CIOL interactions require faculty to recognize their own cultural biases and shift from a "deficit mindset" to an "assets mindset" when engaging with multicultural students (Mann & Mennicke, 2022). These interactions focus on communication strategies, social presence, and course design. Effective strategies include instructors sharing personal experiences, providing timely feedback, and addressing students by name to foster safe, inclusive environments (Van Houweling, 2021). Personalized and supportive instructor interactions help students feel valued and recognized (Pacansky-Brock et al., 2020). Peer interactions and activities that encourage self-expression and exploration of others' backgrounds promote social connection (Guo-Brennan, 2022). Combining open discussions, problem-based learning, and reflective activities allows students to present themselves in diverse ways. Universal Design for Learning (UDL) strategies further enhance inclusion by offering multiple modalities for assignments, assessments, and interactions (Frechette et al., 2018b).

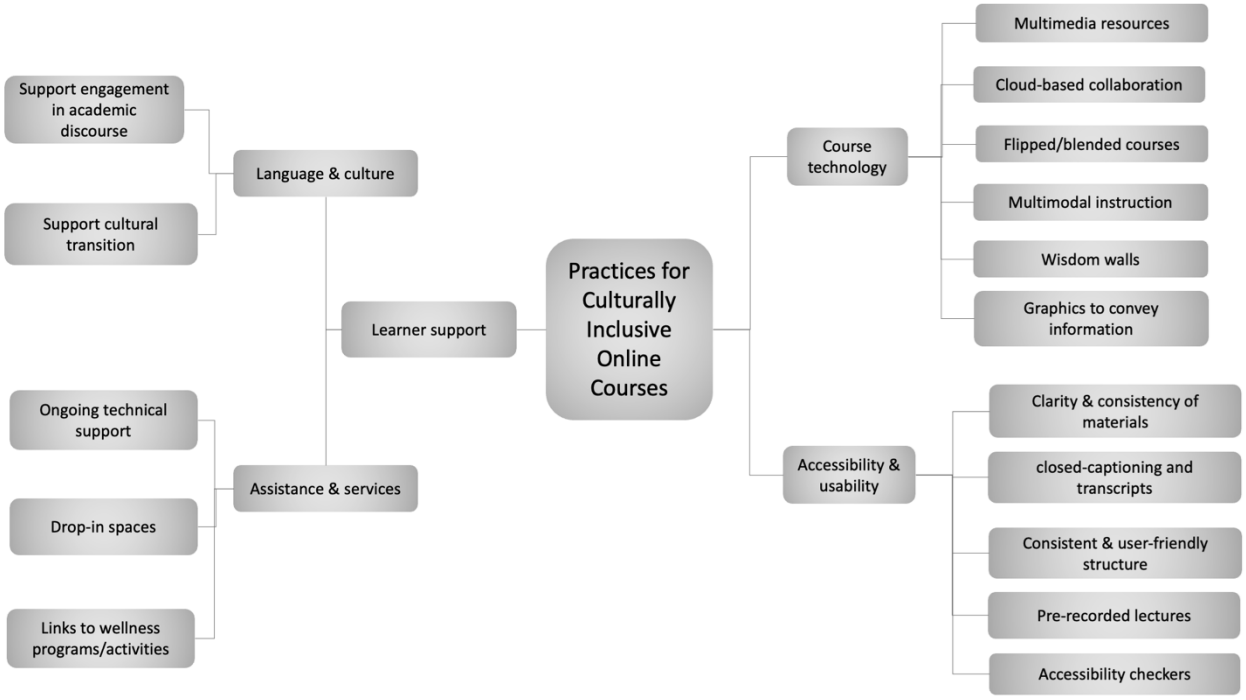
Assessment and Measurement

The selected research offers recommendations for enhancing assessments to promote cultural inclusion in OL. Assignments should honor learners' communities, cultures, and individual stories (McCarron & Yamanaka, 2022; Pacansky-Brock et al., 2020) and assess knowledge of "cultural worldviews" (Morong & Desbiens, 2016). Flexible, student-friendly assessments that amplify learner voices, such as journals, collaborative projects, reflections (McCarron & Yamanaka, 2022), portfolios (Jabbar & Mirza, 2019), life narratives, interviews, video news, and learning diaries (Koponen, 2020), or problem-based learning (Hunt & Oyarzun, 2019) are recommended. Problem-based tasks should be relatable to students' cultures and address diverse populations' needs (Finkelstein et al., 2022; Abramenka-Lachheb & de Siquiera, 2022).

Other strategies include offering multiple means for learners to demonstrate learning (Gronseth, 2018), combining individual and group assignments, and allowing submissions in creative formats such as songs, poetry, or video (McCarron & Yamanaka, 2022). Assignment expectations should be clear, detailed, and include examples (Lowenthal et al., 2020; Hashlamoun, 2021). Inclusive grading practices involve integrating equality and cultural considerations into rubrics, grading group projects based on individual contributions, and providing assertive or audio feedback (Abramenka-Lachheb & de Siquiera, 2022; Knauf, 2016). Flexible deadlines also enhance inclusivity for international students (Sadykova & Meskill, 2019). Last, reflective assessments are recommended to allow different ways for students to demonstrate learning, which respects diverse communication styles (Kumi-Yeboah et al., 2018).

Figure 7

Design Guidelines for Course Technology, Accessibility and Usability, Language And Culture, and Assistance and Services.



Course Technology

The use of technology provides enhanced opportunities for instructors and learners to connect with their peers from different cultures (Chang & Benson, 2022). Online and mixed-mode courses also make learning more accessible for students in communities with fewer resources (Yesmin & Khan, 2021). Best practices shared in the literature include offering multiple channels of communication through an LMS (Dream et al, 2017, Dreamson et al, 2018), visually enhancing courses by incorporating images of order and symmetry (Hashlamoun, 2021) by using graphics to convey meaning (Lowenthal et al, 2020), and creating a space for students to share advice with future students (Pacansky-Brock et al, 2020). The use of video can give the instructor as well as students a chance to introduce themselves and their unique background (McCarron & Yamanaka, 2022). Instructional videos were perceived as more humanistic if they are six minutes or less and have a personal feel (Pacansky-Brock et al, 2020).

Accessibility and Usability

The selected research underscores the importance of consistently applying Universal Design for Learning (UDL) strategies to create a culturally inclusive learning environment (Dawson, 2022). Providing content and assignments in multiple formats enables diverse engagement and enhances accessibility. Allowing students to choose assignment formats, interactions, and assessments improves perceptions of learning and increases their willingness to complete online assignments (Al-Azawei et al., 2016). Ensuring usability features, (e.g., properly formatted headings) and using accessibility checkers can support this process (Lowenthal et al., 2020). Additionally using simple language and visual aids and avoiding idioms and culturally specific references that may exclude non-native English speakers was discussed (Kumi-Yeboah et al., 2018).

For video content, closed captioning and pre-recorded videos that can be paused and rewatched are critical for equitable access (Foltz & Brown, 2022). Instructors should evaluate how content sounds with screen readers, particularly non-text elements like images and charts (Lowenthal et al., 2020). Including a syllabus statement with links to the accessibility of required technologies is also recommended (Lowenthal et al., 2020). Overall, UDL principles provide a foundational approach to fostering inclusivity for diverse learners.

Learner Support

The research also provides insights on steps that educators can take to be supportive of students from a variety of cultural backgrounds. Culturally diverse students may benefit from guidance that helps them surpass any language barriers and adapt to the culture and discourse of education in the country where they are receiving instruction (Kang & Chang, 2016, Sadykova & Meskill, 2019). Educators can also maximize support by providing multiple channels of communication for students and ensuring that students are connected with other resources that will help them achieve success, such as campus programs, wellness, and tech support (Cochrane & Maposa, 2018, Gourlay et al, 2021). Students can be directed to multicultural advising and tutoring that acknowledge and address cultural and linguistic differences (Munger et al., 2021).

Discussion

The discussion is organized into five sub-sections. Together, these sections highlight critical findings and actionable insights for advancing culturally inclusive online education.

Cultural Representation in Online Learning

Our findings indicate that cultural minorities are often categorized broadly as international students. This indicates insufficient attention toward domestic cultural diversity within online learning environments including African, indigenous, Asian, and Hispanic populations. Domestic cultural diversity specifically recognizes that significant cultural differences exist among students who are citizens of the same country whereas international diversity focuses on students from foreign countries. These observations align with Uzuner's (2009) assertion that insufficient emphasis has been placed on examining domestic cultural diversity. Moreover, the tendency to segment cultural inclusion interventions based on race, rather than adopting a holistic approach that acknowledges individual differences among minority students, is still evident (Uzuner, 2009). Our findings highlight a notable lack of attention to ethnic groups in the literature, emphasizing the need for a more comprehensive exploration of cultural inclusion. In online learning environments, cultural representation is critical because students often engage with course materials, instructors, and peers through mediated interactions. Without intentional recognition of diverse cultural identities, online courses risk reinforcing a "one-size-fits-all" approach that limits student engagement, belonging, and equitable participation.

Theoretical Foundations of Cultural Inclusion Practices

A key finding is the increasing use of theory to inform CIOL practices. Unlike Kumi-Yeboah et al. (2020), who found cultural inclusion practices were not purposefully integrated into online teaching, our research highlights a growing trend among scholars to intentionally base interventions on established theories. These include learning, cultural, critical, social justice, and instructional theories. The use of multiple theories reflects the complexity of culturally inclusive learning, aligning with Dreamson et al.'s (2017) view that online learning environments function as sociocultural spaces.

The incorporation of diverse theories in the literature is driven by three factors: (1) the multifaceted nature of culturally inclusive learning, involving power dynamics, cultural contexts, and instructional design; (2) the need for holistic approaches to examine interactions among learning, culture, and critical awareness; and (3) the importance of critical theories in addressing oppression, privilege, and inequity. Future research should focus on using single theoretical frameworks in individual studies to advance instrumentation.

Practices for Fostering Cultural Inclusion in Online Learning

Consistent with Yamo et al. (2022), our findings highlight the importance of community building, networking, and representation in communications to engage culturally diverse students. Our research extends beyond communication and representation, compiling research-based practices to guide researchers, instructional designers, and faculty in shaping future work. Key practices include incorporating culturally relevant learning objectives, providing personalized materials that reflect diverse cultures, facilitating intercultural group work, enhancing instructor social presence and support, and promoting flexible, risk-free interactions. Overall, our findings reveal significant advancements in cultural inclusion and social constructivist practices, such as problem-based learning and peer-to-peer interactions, aligning with Dreamson et al. (2017).

The Role of Technology

While earlier studies focused on the instrumental role of certain technologies (e.g., LMS, MOOCs) our findings highlight course-level technology-infused pedagogies, such as video narratives, video feedback, and cloud-based collaboration, which enhance learner

engagement and intercultural dialogue (Marrone et al., 2013). However, few studies have examined the potential of virtual reality, augmented reality, social media, and generative artificial intelligence to create equitable OL experiences and address feelings of isolation reported in prior research (Reedy, 2019).

Building on Marrone et al. (2013), this review identifies specific practices that align with UDL principles. These include flexible access to content, interaction, and response methods (Dawson, 2022), increased use of accessibility checkers (Kieran & Anderson, 2018), accessible content and activities for Indigenous students (Gronseth, 2018), and recorded lectures with captions and transcripts. Together, these findings offer a comprehensive perspective on how overarching principles and targeted practices contribute to cultural inclusion in online learning environments.

Complementing Course Evaluation Frameworks

With students from diverse cultural backgrounds participating in online learning, it is essential for faculty and instructional designers to adopt generalizable guidelines to foster inclusivity. Figures 6 and 7 help higher education institutions worldwide to guide the implementation of instructional strategies to CIOL. These practices could be aligned with existing course review frameworks (e.g., Quality Matters, OSCQR) or adapted for specific institutional needs. Additionally, the practices identified in this review provide higher education administrators with a foundation for faculty development programs that offer theoretical insights, practical knowledge, and actionable strategies to enhance the cultural relevance of online courses and programs.

Implications for Key Stakeholders in Higher Education

Faculty can integrate culturally inclusive practices by adapting course content to reflect students' diverse cultural backgrounds. Strategies like intercultural group work and personalized communication can enhance engagement and learning outcomes. Instructional designers can guide their practice by applying the research-based strategies (Figure 6 and 7) when creating learning objectives, content, and assessments. Administrators are advised to pilot faculty training on culturally responsive pedagogy and emphasize cultural inclusion in institutional policies, faculty evaluations, and course review processes.

Limitations

This study has four limitations. First, our search strategy was limited to articles published in English, potentially excluding foundational studies conducted by non-English speaking researchers. Second, the exclusion of conference proceedings and dissertations aimed at ensuring academic rigor might have resulted in overlooking valuable insights from emerging research. Third, our choice of search terms may have limited our results by failing to find articles that use different, yet related, keywords or subject terms. For example, our search for cultural "inclusion" may not have generated results that emphasize cultural "relevance" or "sensitivity." While we conducted both keyword searches and subject searches, it's possible that this language still limited our findings. Fourth, cultural background influences learning preferences and how students engage with online learning environments. In collectivist cultures (e.g., Asia, Africa, South America), learning is often viewed as a shared, team-oriented effort. In contrast, individualist cultures (e.g., US, Canada, Australia) tend to emphasize personal success (Dunn & Brown, 2021). Green et al. (2017) also highlight differences between high-context cultures (e.g., Latin America, Middle East) and low-context cultures (e.g., Western Europe, US) in terms of learning preferences and

expectations. These cultural distinctions may create challenges for students in online learning, particularly in areas such as academic integrity and communication. However, our review did not distinguish whether these challenges arise from cultural background or individual learning preferences.

Future Research Opportunities

Community-based approaches and participatory research designs that involve close collaboration with diverse student populations can be conducted to gain a deep understanding of students' contexts, perspectives, and needs. Moreover, design-based research studies could be conducted to enhance the existing practices identified in our literature review through a series of iterative cycles of revision and improvement aimed at informing existing theories that predict/explain cultural inclusion in OL.

Similarly, research is needed to examine how emergent technologies (Generative AI) can be leveraged to create more inclusive online learning experiences. Researchers could examine specific CIOL practices (listed in Figures 6 and 7) and measure impacts on learning engagement, motivation, and learning while controlling variables such as learners' cultural background, prior knowledge, and/or cultural inclusion awareness. Future researchers could also use existing adoption frameworks (e.g., UTAUT, Planned Behavior) to facilitate the application of CIOL practices in courses in modalities that include digital components (e.g., online, mixed mode, video-based).

Conclusion

The present study has four key conclusions. First, most of the literature on CIOL has included students with diverse nationalities, but insufficient emphasis has been placed by researchers on examining domestic cultural diversity. Second, research on CIOL has been informed by different theoretical frameworks, indicating its multifaceted nature but evidencing potential challenges to advance knowledge due to a multiplicity of factors, interventions, and outcomes. Third, technology-infused CIOL pedagogies at the course level can be leveraged to facilitate learner's engagement and learning, but emergent technologies such as virtual reality, augmented reality, and generative artificial intelligence have been largely excluded. Last, existing instructional design practices in CIOL highlight the significance of community building, networking, and representation of diverse students and perspectives in course communications.

While these findings synthesize the current state of CIOL research, they also point toward broader implications. Theoretically, there is a pressing need to consolidate CIOL scholarship under shared conceptual frameworks. The current fragmentation across cultural, educational, critical, and social justice lenses risks limiting cumulative knowledge. Future research should advance integrative theoretical models that connect culturally relevant pedagogy, universal design, and critical perspectives to ensure CIOL develops as a coherent, evidence-based field.

For practice and policy, the findings highlight the urgency of embedding cultural inclusion into the design of online learning at both institutional and course levels. Institutions should invest in faculty development programs that prepare instructors to adopt culturally responsive pedagogies, particularly in STEM disciplines where inclusion remains limited.

Policies that encourage representation, multilingual resources, and technology-mediated intercultural collaboration can further ensure that online learning environments promote equity rather than reproduce exclusion. Moreover, emerging technologies such as virtual reality, augmented reality, and generative AI should not be treated as neutral tools but as design spaces where inclusive practices can be systematically tested, refined, and implemented.

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A Predictive Model to Explain Student Persistence in Blended and Online Courses in Higher Education

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Abstract
This study sought to identify the significant predictors of students' persistence in blended and online courses in higher education. Drawing from Choi's model (2016), a structural model, comprising eight predictive and three moderating variables, was tested. The sample was composed of 348 students enrolled at two French-speaking Canadian universities who completed an online questionnaire. Data were analyzed using partial least squares structural equation modelling (PLS-SEM) and partial least squares multigroup analysis (PLS-MGA). The findings suggest that learner autonomy, student satisfaction, perception of a Community of Inquiry, and family responsibilities are the primary factors influencing student persistence in blended and online courses. Furthermore, the model explains between 9.3% and 46.4% of the variance in persistence, depending on whether we examine the moderating effect of age, gender or course modality. The paper presents recommendations for institutions and faculty seeking to enhance student persistence in blended or online courses.

Keywords: Higher education, online courses, blended courses, student persistence factors

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Distance education has evolved with technological developments in communications (Lee, 2017; Moore, 2018a). The most recent generation of distance education—the one mediated by Web technologies—has enabled higher education institutions to offer new course modalities to their students (Lakhal & Bélisle, 2020). If we consider the proportion of content delivered online, as proposed by Allen et al. (2016), in addition to traditional face-to-face courses where no or little online technology is used (0% to 29% of content delivered online), two types of courses are now available to students in higher education: blended or hybrid (courses with a combination of face-to-face and online modalities where a substantial proportion [30 to 79%] of the content is delivered online), and online (courses where 80% of the content is delivered online). These two modalities are on the rise as indicated by the number of students enrolled in these courses. For example, in Canada, many post-secondary students had experienced at least one fully online course (40%) or at least one blended (36%) in 2024 (Johnson, 2024). This is a marked increase compared to the 17% of students who were enrolled in at least one credited blended or online course (BOC) in a Canadian post-secondary institution during the 2016-2017 academic year (Bates et al., 2019). A similar phenomenon is observable in the United States, where 31.6% of higher education students in 2016 were enrolled in at least one BOC (Seaman et al., 2018). This proportion has increased to 54% by 2022 (National Center for Education Statistics, 2023).

Despite the growing popularity of BOC, it is imperative to acknowledge the challenges associated with these modalities. A recurring issue that has been identified is the lack of student persistence (Delnoij et al., 2020; Heilporn & Lakhal, 2022; James et al., 2016; Shaikh & Asif, 2022; Xavier & Meneses, 2020), especially in online courses. Notwithstanding the heterogeneity of definitions and calculation methods employed, persistence rates observed are often lower in BOC than in face-to-face courses (Fan et al., 2024; Papi et al., 2022; Park & Choi, 2009). Studies which have sought to compare student persistence rates between BOC and face-to-face courses reported a discrepancy in favor of the latter (Ali & Smith, 2015; Garratt-Reed et al., 2016; James et al., 2016; Mohammadian et al., 2021; Wladis et al., 2017; Xu & Jaggars, 2011).

Literature Review

Several scholars have examined the factors associated with persistence in BOC within the context of post-secondary education. According to several literature reviews published in the last two decades (Bawa, 2016; Hart, 2012; Lee & Choi, 2011; Paris, 2024; Shaikh & Asif, 2022; Xavier & Meneses, 2020), a variety of factors have been identified as both facilitators and barriers to student persistence in higher education BOC. Consequently, persistence can be regarded as a multifaceted phenomenon, influenced by a range of factors contributing to student persistence or non-persistence (i.e., dropout). To enhance comprehension of the factors that contribute to students' persistence in their respective courses or programs, and to facilitate understanding of this intricate phenomenon, a number of theoretical models have been developed. These models identify the major factors that influence persistence and illustrate the dynamic aspects of the phenomenon (Xavier & Meneses, 2020).

In 1989, Kember proposed the *Longitudinal Model of Individual Departure*, a longitudinal model designed to explain the persistence of students enrolled in distance education. The author posits that the student population enrolled in distance education is non-traditional, i.e. generally older and usually studying part-time. The model identifies four categories of variables that explain the decision to persist or dropout: the characteristics of the student population, goal

commitment, the academic and social environment, and finally, the evaluation of costs and benefits. In 2003, Rovai proposed a *Composite Persistence Model* with the aim of explaining the persistence of the non-traditional student population, specifically in the context of online learning. This model incorporates two models of dropout in higher education, namely those of Tinto (1993) and Bean and Metzner (1985). Rovai's model comprises four components, two of which are present prior to admission (student characteristics and student skills) and two after admission (internal and external factors). The decision to persist is determined by the internal factors, and indirectly by the other three components of the model. According to Rovai (2003), persistence in online learning involves a considerable number of interactions between the many factors.

In 2007, Park proposed an update to Rovai's model, which evolved into the *Revised Model of Dropouts from Distance Learning in Organizations* (Park & Choi, 2009). This model was designed for non-degree online programs for adults learners. According to Park and Choi (2009), a review of the extant literature revealed that the Rovai (2003) model requires some adjustments. Park's model retains the categories of the Rovai model; however, due to a lack of empirical evidence, certain variables intrinsic to these components are extracted from the model and the structure and relationships between the components of the model are significantly reorganized. Finally, in 2016, Choi modified their previous model and proposed a *Framework for Adult Dropouts in a Cyber University*. The most significant modifications consist of the integration of student skills with learner factors (rather than student characteristics), as well as the incorporation of academic performance within the program, which has been demonstrated to exert a direct influence on student persistence. This model focuses on factors affecting higher education, non-traditional adult learners' decisions to persist in online formal (i.e. credited) degree programs.

Several conclusions may be deduced from these models. First, the focus of all models is on non-traditional students. According to Rovai (2003), these students are typically defined as individuals over the age of 24 who often have family and professional responsibilities and are enrolled on a part-time basis. It can be argued that the student populations in BOC are diverse and do not exclusively consist of non-traditional students. As previously stated, a significant number of universities and colleges have adopted these modalities within their respective programs. Then, despite the preponderance of non-traditional students within numerous BOC or programs across various institutions, the traditional student demographic remains significant in many BOC. It is also important to consider their characteristics. Second, as argued by Choi and Kim (2018), conceptualizing the important factors in the decision to persist remains an ongoing process until scholars reach a consensus based on more empirical evidence. Only a limited number of studies have empirically tested the overall viability of these above-mentioned models (Rawal & Razak, 2022). Further research is therefore needed to validate the effectiveness and efficacy of these models. Third, as noted above, persistence is the result of a multifaceted process involving many factors and complex interactions. In this regard, some of the models indicate that a factor may not have a direct effect on persistence but may significantly influence another factor that does have a direct and significant effect. Also, according to the literature review mentioned above, some variables have a mediating or a moderating effect in relation to persistence. However, most studies do not measure indirect effects, the effects of several factors at the same time, or mediating and moderating effects, often for methodological reasons. To develop a deeper understanding of persistence in BOC, it is necessary to examine various relationships

between multiple variables. Therefore, it seems important to consider the factors for all kinds of students (traditional and non-traditional), the different characteristics proposed by the models, and also the possible relation between the categories of characteristics.

The study's objective is to provide a student persistence model in BOC that draws upon the one proposed by Choi (2016). This model was selected since it has been developed by building on the empirical results of all the other models (Rawal & Razak, 2022), and because it was designed for formal education, which is the case in this study. To the best of our knowledge, only a small number of studies (Choi & Kim, 2018; Choi & Park, 2018; Choi, 2021) have validated this model in order to identify factors associated with student persistence within online courses in formal higher education, and all of these studies were conducted by the model developer. Furthermore, there have been no studies published involving blended courses. Accordingly, to furthering knowledge, this study will validate a predictive model of student persistence in the context of BOC in higher education by answering the following question:

> Which factors are significant predictors of students' persistence in BOC in higher education?

Research Model

According to Choi (2016), four categories of factors explain student persistence. First, these include learner factors, comprising sociodemographic characteristics, basic scholastic aptitude, and studying motive. Second, external factors, defined as aspects that occur outside the classroom are included, such as variables deemed to be environmental like financial situation, employment status, or family responsibilities. Third, internal factors encompass characteristics associated with the studies and are related to the educational institution, faculty, and courses, such as the course's pedagogical design or institutional support. The final factor is Grade Point Average (GPA), indicating scores in courses on average, as an outcome factor. As illustrated in Figure 1, the research model incorporates factors from each of these categories. Furthermore, the selection of factors within each category was informed by (a) the findings from the most recent literature review (Bawa, 2016; Hart, 2012; Lee & Choi, 2011; Paris, 2024; Shaikh & Asif, 2022; Xavier & Meneses, 2020); (b) the results of studies concerning the selected factors; and (c) the need to address gaps observed in previous studies (e.g. limited focus on blended courses, lack of moderator testing, and inconsistent results for some factors across studies).

Persistence

As indicated by Roland et al. (2015), there are many definitions and operationalizations of persistence and these may refer to various forms of behavior depending on the perspective adopted. In this study, persistence in BOC is examined from the student's perspective, which relates to the student's decision to continue studying (Kharchi, 2021). In this regard, persistence is operationalized as "the intention to complete the online course in which the student is enrolled" (Lakhal et al., 2021, p. 4).

Learner Factors

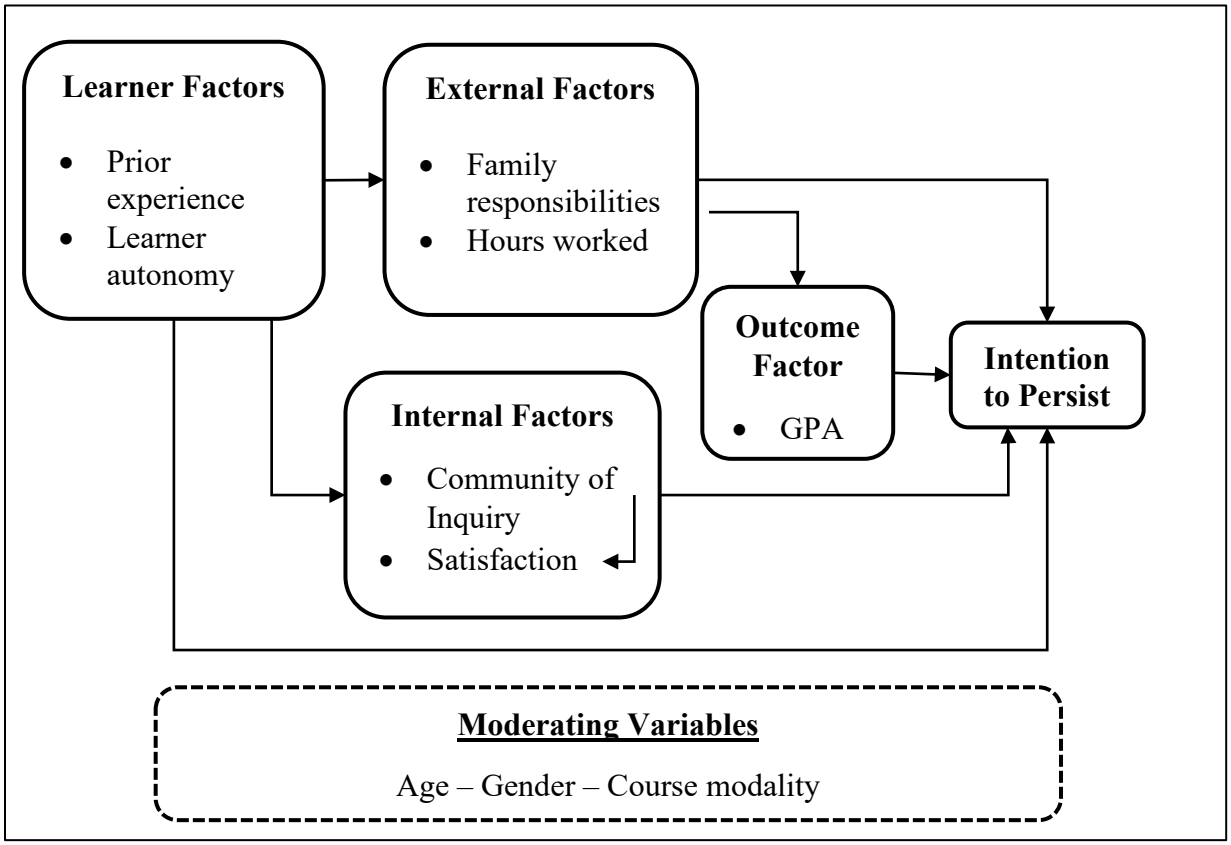
The relation between learner factors and persistence is not likely to be direct (Kember, 1989). All previously presented models demonstrate an indirect relationship between the learner factors and persistence. According to Choi (2016), the learner factors exert an indirect influence on persistence, with this influence being exerted through both internal and external factors.

Nonetheless, basic scholastic aptitude and studying motivation can be regarded as significant predictive variables for the successful completion of BOC (Choi & Kim, 2018). Consequently, it is posited that the integration of these two factors in learner characteristics should result in the addition of a direct link between learner factors and persistence.

Accordingly, this study will first examine the effect of *prior experience* on persistence and internal factors. Prior experience, defined as the number of courses previously taken, impacts persistence in online courses (Lee & Choi, 2011; Shaikh & Asif, 2022). It remains unclear whether this is the case for blended courses, as no studies, to our knowledge, have been conducted to investigate this relationship. Studies also demonstrated that previous experience with BOC is positively related to learning satisfaction (Landrum, 2020; Wang et al., 2013; Zhu, 2017) and Community of Inquiry (CoI) presences (Dempsey & Zhang, 2019; Salloum, 2011). The validity of these associations is expected to be confirmed in the present study.

Figure 1

Research Model



Secondly, this study will examine the effect of *learner autonomy* on persistence, and on internal and external factors. According to Andrade and Bunker (2009), learner autonomy is characterized by a variety of learner interventions in their own learning processes such as the establishment of learning objectives, the development of learning plans, the selection of

educational materials and activities, the identification of resources to support learning, the management of time for learning, and the self-assessment of the learning process. As indicated in literature reviews (Hart, 2012; Lee & Choi, 2011; Xavier & Meneses, 2020), students who possess autonomy-related attributes demonstrate higher persistence, suggesting a potential relationship between learner autonomy and persistence in BOC. Research has also demonstrated a positive association between learner autonomy and CoI (Jin et al., 2023; Özüdoğru, 2021; Turk et al., 2022), as well as with student satisfaction (Abuhassna, 2020; Chen et al., 2010; Ke & Kwak, 2013).

External Factors

External factors have the potential to exert an influence on internal factors, GPA, or persistence according to consulted models. An important external factor associated with persistence is personal commitment, such as the number of *hours worked* and *family responsibilities* (Bawa, 2016; Hart, 2012; Lee & Choi, 2011; Paris, 2024; Shaikh & Asif, 2022; Xavier & Meneses, 2020). Balancing studies with other commitments such as full-time work and having family obligations increases the risk of dropout (Papi et al., 2022). However, as indicated by the findings of various studies (Kim & Park, 2015; Papi et al., 2022; Park & Choi, 2009; York, 2014), the presence of familial support is more likely to account for the phenomenon of persistence than being married or having children. This suggests that students perceiving fewer family responsibilities demonstrate greater persistence.

Regarding the influence of employment status on persistence, Sultan & Hagger (2013) results showed that being employed was a barrier to persistence, while Lee & Choi (2011) indicated that it is full-time work that affects persistence. These findings suggest a negative relationship between hours worked and student persistence.

Finally, despite the existence of a direct link between external factors and GPA, as shown by Choi's model, the underlying mechanisms through which these external factors influence academic performance remain to be fully elucidated. While it can be hypothesized that a difficult conciliation between studies and other commitments such as employment or familial responsibilities may potentially have adverse consequences on academic performance, further validation of this association is required.

Internal Factors

Just like external factors, internal factors have a direct effect on persistence (Rovai, 2003; Park, 2007; Choi, 2016). *Student satisfaction* involves diverse aspects of BOC and it may be understood as a multidimensional construct. In this study, we examine satisfaction in terms of four components as proposed by Bolliger and Wasilik (2012): (a) the teacher, (b) the technology (c), the course structure, and (d) overall satisfaction. Besides being viewed as a key measure of learning outcomes in online courses (Lewis, 2019; Wei & Chou, 2020), student satisfaction has been repeatedly identified as a strong, direct, significant and positive factor for persistence in online courses in consulted literature reviews. Moreover, recent studies have confirmed this relationship (Armstrong et al., 2021; Choi & Kim, 2018; Choi & Park, 2018; Lakhal et al., 2021; Paris et al., 2025). It's not clear whether the effect is similar in blended, but we assume it is.

Course design and interaction are also mentioned as internal factors influencing persistence (Xavier & Meneses, 2020). The *CoI* framework is a particular learning environment

based on the principles of the social constructivist paradigm of learning and the three presences of the model correspond to various types of interaction according to Saadatmand et al. (2017). As mentioned in previous research (Paris et al., 2025), studies that examine the relationship between CoI and persistence reported a positive effect of one or more presences on persistence, but this effect is most often indirect, especially when the relationship is mediated by student satisfaction. Accordingly, although Choi's models do not illustrate the potential links between variables in the same category, we will examine this relationship.

Academic Performance

Academic performance, most often measured by GPA, has been identified as an outcome factor affecting directly persistence, as posited by Choi (2016). According to Choi and Kim (2018), this addition was necessitated by empirical evidence from numerous studies demonstrating that GPA is a salient predictor of students' decisions to persist or drop out in distance education programs in higher education. Literature reviews have on many occasions highlighted that learners with lower academic results are more prone to drop out from online classes (Hart, 2012; Lee et al., 2011; Shaikh & Asif, 2022; Xavier & Meneses, 2020). Accordingly, the research model will examine the extent to which GPA has a direct influence on persistence.

Moderating Variables

Several researchers have directed their attention toward an examination of the disparities in *age* and *gender* with respect to persistence (Shaikh & Asif, 2022). There is no clear consensus in the existing literature on the impact of such factors: Some report that learner characteristics have a significant impact on the decision, while others claim that these characteristics have only a small or indirect impact, or no impact at all (Papi et al., 2022; Park & Choi, 2009). Methodology employed can also have an impact on the results obtained, given that indirect effects are not always quantifiable. As demonstrated by Paris et al. (2025), we posit an indirect effect of age and gender on student persistence and, more specifically, a moderating effect.

The research results of James et al. (2016) suggest that blended courses are associated with higher retention rates than online courses. Since few studies have addressed this issue, more research is needed to evaluate this effect. In this research, course modalities is a dichotomous variable (blended versus online). Therefore, we will look at the moderating effect of course modalities on the research model.

Method

Participants

Data collection was conducted during the summer and fall 2023 semesters in two French-speaking Canadian universities. An online questionnaire was developed; all students enrolled in a BOC during the aforementioned semesters were invited by email to complete it. The online questionnaire was available for a period of five weeks and took approximately 15 minutes to complete. The participants were permitted to complete the questionnaire in one setting or return to it as many times as necessary, and they received reminder messages during the data collection period. At the end of the data collection period, five $50 gift cards were drawn at random among the 348 participants who completed the questionnaire. Descriptive statistics of the sample are shown in Table 1.

Table 1

Participant's Profile

Characteristics	Frequency	Percent
Age		
24 or less	149	42.8
25 or more	199	57.2
Gender		
Women	275	79.0
Men	67	19.3
Course modalities		
Blended	86	24.7
Online	262	75.3

Measures

Most of the data collected derives from simple questions on demographic information (age, gender), the number of courses previously undertaken (prior experience), number of hours worked by week, the current self-reported program's GPA, and the course modality (online or blended). For family responsibilities, participants were invited to provide a response to the following question: *How do you view your family responsibilities?* The response options ranged from 1 (*Not Important*) to 5 (*Very Important*). In addition, we used four existing scales, for which validity and reliability had been established in a previous study. Each one was on a 7-point Likert scale (ranged from 1 [*Strongly Disagree*] to 7 [*Strongly Agree*]). The Learner Autonomy questionnaire, comprised of six items, was taken from Lakhal et al. (2013). Items addressing the CoI presences were taken from a French version (Heilporn & Lakhal, 2020) of the CoI questionnaire developed by Arbaugh et al. (2008). Student satisfaction was measured by twelve items taken from Paris et al. (2025) and the instrument designed to measure students' intentions to persist in their studies was developed by Heilporn and Lakhal (2022) based on the work of Kember (1995) and Lakhal (2019).

Data Diagnostics

The descriptive statistics from the study variables revealed no instances of outliers or extreme values. However, certain indicators (three items for learner autonomy, three items for persistence, and one for CoI) were found to be non-normally distributed, as indicated by skewness and kurtosis values, and upon visual inspection of the P-P plot. The study also encountered one missing data (0.3%) related to intent to persist and six (1.8%) related to gender.

Analytic Strategy

We examined the model (Figure 1) using partial least squares structural equation modelling (PLS-SEM) with SmartPLS® 4 software (Ringle et al., 2024). Moderating effects were assessed using a partial least squares multigroup analysis (PLS-MGA) using the bootstrap method (Hair et al., 2024).

PLS-SEM was deemed to be suitable for this study given its exploratory nature, which involves several latent variables to be explained simultaneously, with some indicators exhibiting non-normal distribution (Chin & Newsted, 1999; Hair et al., 2022). It is also appropriate to test some study hypothesis because PLS-SEM allows detecting mediating and moderating effect in parameter estimates (Cheah et al., 2020). In the present study, we used 5,000 random subsamples and implemented a one-sided significance test at the 0.05 level. The significance of the path coefficient estimates was determined by a bias-corrected and accelerated (BCa) bootstrap interval. Also, *mean value replacement* was used to handle missing data.

Results

We adopted the proposed assessment techniques specifically tailored to PLS-SEM's prediction-oriented nature to evaluate the models, given the theoretical limitations of model and exact fit testing in PLS-SEM (Hair et al., 2019, 2020; Sarstedt & Cheah, 2019). We also followed the guidelines provided by Hair et al. (2024) for the subsequent PLS-MGA analysis.

Measurement Model Assessment of Latent Variables

The analysis of the measurement model was conducted by assessing the item loadings and their significance (loadings ≥ .70 and significant two-tailed test at the 5% level), the internal consistency reliability (Cronbach α and composite reliability > .70), and the convergent (average variance extracted > .50) and discriminant (heterotrait-monotrait ratio of correlations < .90) validity of each construct (Hair et al., 2020).

The preliminary analysis indicated that all item loadings were significant, but eight items were below the threshold (0.70) (one for learner autonomy, six for CoI, and one for intent to persist). Furthermore, three items related to the CoI scale were below 0.50. These three items were removed, along with those related to learner autonomy and persistence. Removal of other indicators did not result in a relevant increase in internal consistency reliability or convergent validity of the construct. Model was re-estimated, and Table 2 demonstrates that all constructs achieved satisfactory values for other measurement model assessment.

Table 2

Internal Consistency Reliability, Convergent and Discriminant Validity for Latent Variables

	α	CR	AVE	1	2	3	4
1. Learner autonomy	0.89	0.92	0.70	1			
2. CoI	0.97	0.97	0.52	0.24	1		
3. Satisfaction	0.96	0.97	0.70	0.27	0.87	1	
4. Persistence	0.86	0.90	0.70	0.38	0.37	0.45	1

Note. (α) Cronbach alpha, (CR) Composite reliability, (AVE) Average variance extracted, (CoI) Community of Inquiry.
The HTMT ratio values for pairs of constructs are presented in columns 1 to 4, with all confidence intervals' upper bounds being smaller than 0.90.

Structural Model Analysis

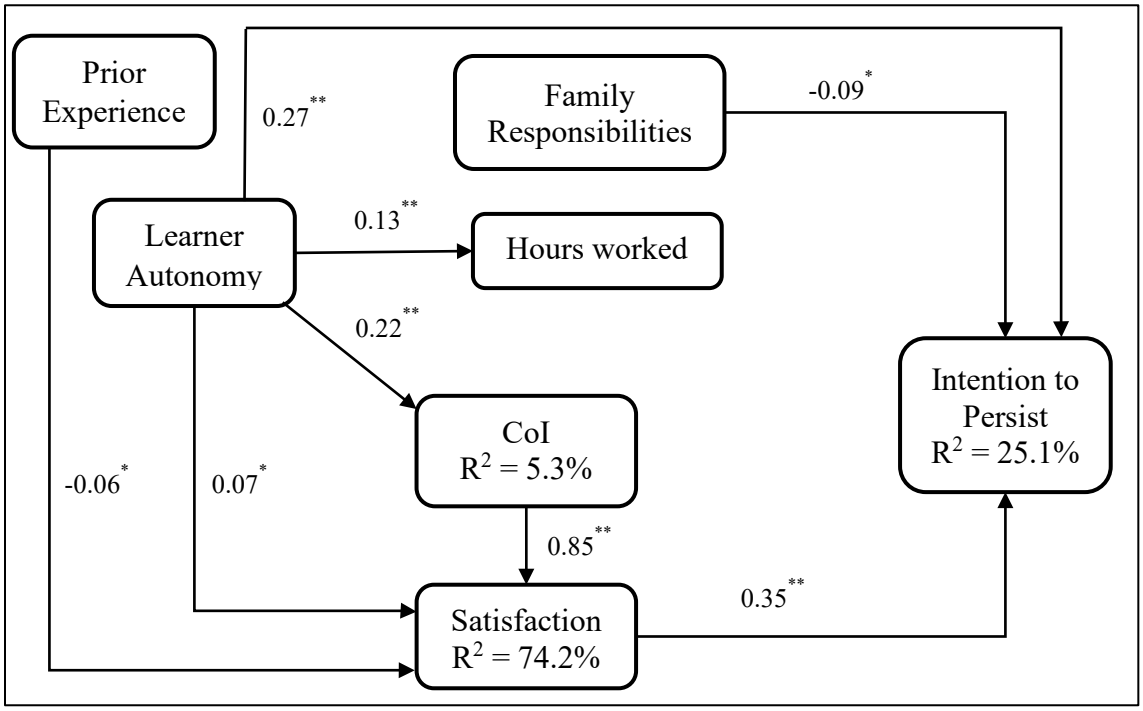
The structural model was assessed by the path coefficients significance and the variance of the endogenous construct. Values for the significant endogenous construct (R^2) and significant path coefficients are indicated in Figure 2 (all values are presented in Appendix B). As shown by the R^2 values, the predictive student persistence model explained 25.1% of the variation in persistence in BOC, 74.2% of student satisfaction, and 5.3% of CoI.

Regarding learner factors, the effect of prior experience on students' satisfaction (β = -0.06, $p < .05$) was found to be significant. However, prior experience did not emerge as a predictive factor of CoI (β = 0.05, $p = .156$) or persistence (β = -0.01, $p = .417$). Concerning the second learner factor, the effect of learner autonomy on family responsibilities was non-significant (β = 0.02, $p = .313$), whereas the effect on hours worked (β = 0.13, $p < .01$), CoI (β = 0.22, $p < .01$), student satisfaction (β = 0.07, $p < .05$), and persistence (β = 0.27, $p < .01$) were all significant and positive.

The analysis yielded a significant result concerning external factors: the perception of the magnitude of family responsibilities negatively predicts the intention to persist in BOC (β = -0.09, $p < .05$). However, the relationships between family responsibilities and GPA (β = -0.03, $p = .315$), hours worked and GPA (β = -0.04, $p = .209$), as well as hours worked and persistence (β = -0.07, $p = .068$), were non-significant.

Figure 2

Structural Model Significant Results for All Respondents



Note. 1. * $p < .05$, ** $p < .01$. 2. CoI (Community of Inquiry).

The research model considered the effects of internal factors on student intent to persist. In regard to the effect of student satisfaction, the relationship was found to be significant (β = 0.35, $p < .01$) whereas the effect of CoI was not (β = -0.02, $p = .437$). The model also revealed a significant impact of CoI on satisfaction (β = 0.85, $p < .01$).

With respect to the effect of academic performance, measured by GPA, it was not a significant predictor of student intent to persist in BOC (β = -0.04, $p = .182$).

Finally, Table 3 displays the total effects of all factors on persistence. In addition to the three previously mentioned factors with a significant direct effect on intent to persist, COI has also a significant total effect (β = 0.30, $p < .01$). This suggests an indirect effect of CoI on intention to persist when mediated by satisfaction.

Table 3

Total Effect of All Variables on Persistence

Variables	Total effect (β)	*p value*
Prior experience	-0.00	0.426
Learner autonomy	0.35	< .01
Family responsibilities	-0.09	< .05
Hours worked	-0.07	0.069
Community of Inquiry	0.30	< .01
Satisfaction	0.35	< .01
GPA	-0.04	0.176

PLS-MGA Results

PLS-MGA (bootstrap method) was utilized to assess the moderating effect of age, gender, and course modality. Prior to the analysis, the measurement invariance of composites (MICOM) procedure (Hair et al., 2024) was applied to assess measurement invariance when conducting PLS-MGA. All model results met the criteria to assume partial measurement invariance. We therefore proceeded to compare the variance of intention to persist between groups and the total effects of each factor by groups when this difference was deemed significant. The results of the assessment of the differences across the specified groups are displayed in Table 4 and 5.

Regarding age, PLS-MGA revealed no statistically significant difference in intention to persist between students aged 24 and under and those aged 25 and over (R^2 diff = 0.04, p diff = .37). However, the findings indicated discrepancies with the two other moderating variables observed.

First, the results demonstrated a statistically significant difference in the intention to persist between women and men (R^2 diff = -0.21, p diff < .01). The total effects that differed

statistically are hours worked (β diff = 0.19, *p* diff < .05), and family responsibilities (β diff = -0.22, *p* diff < .05).

Table 4

Difference Between Groups in Relation to Persistence

Characteristics	Intent to persist R^2	Difference	*p* diff
Age			
24 or less	0.295	0.039	.370
25 or more	0.256		
Gender			
Women	0.233	-0.213	< .01
Men	0.464		
Course modalities			
Blended	0.093	-0.221	< .05
Online	0.314		

Table 5

Significant Total Effect Difference by Group in Relation to Persistence

Characteristics and factors	Total effect (β) (Women, Blended)	Total effect (β) (Men, Online)	Difference
Gender			
Hours worked	-0.044	-0.238*	0.194*
Family responsibilities	-0.116**	0.104	-0.220*
Course modalities			
Family responsibilities	0.077	-0.125**	0.202*
Satisfaction	0.149*	0.411**	-0.262*

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

For course modalities (blended versus online), a significant difference was found in the intention to persist (R^2 diff = -0.22, *p* diff < .05). The PLS-MGA results revealed two factors that differed statistically across this group, namely, the total effect of family responsibilities (β diff = 0.20, *p* diff < .05) and satisfaction (β diff = -0.26, *p* diff < .05) on intent to persist.

Discussion and Conclusion

The objective of this study was to develop a predictive model to examine student persistence in BOC in the context of higher education. Drawing from Choi's model (2016), one

of the most recent persistence models in higher education for non-traditional online learners, the study sought to identify the direct and indirect relationships with persistence among significant BOC factors derived from recent literature reviews. These factors were prior experience, learner autonomy, family responsibilities, hours worked, CoI, student satisfaction, GPA, age, gender, and course modality. In addition to identifying key persistence factors among BOC students, our results allowed for the detection of certain moderating effects that are the result of specific characteristics. Furthermore, the study's findings enable the proposal of some modifications to Choi's conceptual model.

Factors Affecting Student Persistence

The findings of this study, when considering all respondents, indicated that three factors (i.e., learner autonomy, family responsibilities and satisfaction) within the proposed model exerted a direct influence on student persistence. Therefore, these three factors were the main contributors to persistence, to which we must add the effect of the CoI for its overall significant contribution. Together, these factors predicted 25.1% of the intention to persist.

Consistent with our findings, student satisfaction with BOC has been repeatedly identified in literature review (e.g., Lee & Choi, 2011; Xavier & Meneses, 2020), models (e.g., Rovai, 2003; Choi, 2016), and studies (e.g., Lakhal et al., 2021; Papi et al., 2022) as significantly and positively influencing persistence. This result implies that institutions offering BOC should implement measures to manage student satisfaction to minimize dropouts. In attempting to do so, instructors and administrators need to consider diverse aspects of BOC because satisfaction is a multidimensional construct (Bolliger & Wasilik, 2012). In this study, satisfaction was examined in relation to teacher, technology, course structure, and overall satisfaction, suggesting that all these aspects should be regarded as important.

The findings also corroborate the notion that learner autonomy is a key characteristic for successful learning for students following a BOC in higher education (Andrade & Bunker, 2009; Fotiadou et al., 2017; Ludwig & Tassinari, 2023; Moore, 2018b). This constitutes an innovative contribution, since to our knowledge, no study has examined this relationship with learner autonomy as measured in this study. It is imperative to acknowledge the importance of cultivating learner autonomy within BOC, given its role in fostering students' persistence. Consequently, it is recommended that educational institutions and faculty implement policies and strategies to help develop skills related to learner autonomy among students.

Family responsibilities have an effect on persistence, which is negative ($\beta = -0.09$, $p < .05$): An increase in the perception of the magnitude of family responsibilities has a negative effect on persistence. This result suggests that BOC completion is jeopardized by balancing multiple responsibilities, such as studying and raising a family. This finding is consistent with previous research (Evans, 2009; Luz et al., 2018; Shah & Cheng, 2019) in which students mentioned family responsibilities as a primary, if not the most important, reason for dropping out from an online course or program. Since Park's model in 2007, a direct line from external factors to attrition has been added precisely because many studies have reported that some external factors were important reasons why students decided to drop out. Family responsibilities can interfere with the time commitment needed to participate in courses or complete assignments. Therefore, on the one hand, institutions need to recognize the negative impact of any barriers to full participation in BOC, such as having family responsibilities, and to assist these students in

managing their academic and family responsibilities. They can, for example, develop programs and specialized support for students with family and parental responsibilities and identify those who can benefit from them at the time of admission. On the other hand, whether it's moral support or sharing responsibilities with another family member, findings also demonstrate the importance of family support in relation to student persistence, as pointed out by Papi et al. (2022). The authors provide the example of sharing responsibilities with another family member that allows students to be somewhat freed from certain domestic activities, enabling them to maintain their focus on academic endeavors, thereby contributing to their persistence in their studies.

Although the establishment of a learning environment such as the CoI does not directly impact persistence, it should nevertheless be regarded as a key factor in consideration of its overall effect ($\beta = 0.30$, $p < .01$). This effect is almost as large as the effects of satisfaction ($\beta = 0.35$, $p < 0.01$) and autonomy ($\beta = 0.35$, $p < 0.01$). This can be explained by the very strong effect ($\beta = 0.85$, $p < .01$) of CoI on satisfaction, indicating that a large portion of its variance is explained by this pedagogical design. Thus, in line with other studies (Joo et al., 2011, 2013; Paris et al., 2025), it can be concluded that when the perception of CoI is higher, there is greater satisfaction with BOC, and consequently, an increase in persistence in an ongoing course (i.e., CoI positively and significantly influences students' intention to persist in BOC in higher education when the relationship is mediated by satisfaction). Then, the results of the study demonstrate the benefits of CoI-inspired online learning environments in BOC, especially in promoting persistence.

Considering Student Heterogeneity and Course Modality

When the entire sample is considered, several factors of the research model do not have a significant effect on persistence, although these have been previously identified as having an impact in other publications. However, to draw more precise conclusions, the various moderating effects detected must be examined more thoroughly.

First, this study did not find a difference in persistence as a function of age. The variation of persistence explained by the model is similar for the youngest (24 and under) compared to the oldest (25 and over) students. This suggests that the model should hold for traditional and nontraditional students, given that age (being over 24) has been identified "as one of the most common variables in studies of nontraditional students" (Rovai, 2003, p. 2). Still, it remains unclear what makes age significant in some studies and not in others, and the reasons may be multiple. For example, an overrepresentation of a characteristic that strongly affects persistence in one age group may render the results for age significant in certain contexts. It may also be hypothesized that the age-related differences that existed in the past are of lesser importance in today's context.

The results do, however, show a moderating effect of gender and course modality on persistence. Regarding gender, the model's variables explain persistence better for men ($R^2 = 46.4\%$) than for women ($R^2 = 23.3\%$). The results revealed two barriers to persistence that are specific to each group. The increase in hours worked is an obstacle for men, while it's the increase in family responsibilities that has a negative impact on women. The observed differences may be attributed to divergent perceptions of the student role in higher education among men and women. According to Markle (2015), men give themselves greater flexibility in

allocating their time across various roles and do not experience guilt about spending less time with their families. In contrast, women expressed greater apprehension about their capacity to fulfil their student role in the event of having family responsibilities. Besides, the findings of Burke (2019) indicated that female students were more inclined to report having withdrawn from courses due to familial and parenting duties. Then, the gendered nature of these expectations can explain why this factor exerts its influence solely on women. It can be argued that the aforementioned points also apply to men in the context of employment; that is to say, they place greater emphasis on the value of work in comparison to that of education.

In terms of course modality, the model variables explain little of the variance in persistence for students enrolled in blended courses (R^2 = 9.3%), compared to online (R^2 = 31.4%), where the model performs better. The small amount of variance explained for students enrolled in blended courses suggests that the model variables (selected from online models) are generally less applicable in this context compared to online courses, likely attributable to the inclusion of a face-to-face element. Further studies are necessary to ascertain the applicability of the online model in blended learning. In terms of the differences between the two groups, family responsibilities have a significant impact on those taking an online course, but this impact is not significant in the blended group. One potential explanation for these findings is the interaction effects between certain variables and family responsibilities. Further research is necessary to elucidate this discrepancy. Findings also showed that satisfaction with the course has a greater impact on student persistence online than in blended learning. Again, the possibility remains that certain variables exert a different influence on the degree of satisfaction experienced in blended learning compared to online.

Validation of Choi's Model

Overall, this study demonstrates that learner autonomy, satisfaction, and CoI have a positive impact on persistence among all students enrolled in a BOC in higher education. This is also the case for the degree of family responsibilities, where the impact is negative, except for men (the relationship is not significant). Furthermore, when examining the groups, one additional factor emerges as significant contributor to persistence: hours worked among males.

Our results therefore suggest that Choi's model, designed to examine persistence in the context of an online program, can also be used in the context of a course (although we have mentioned concerns about the blended modality) to examine key predictive variables of persistence. As previously mentioned, the model can also be used for traditional students, since our result showed no difference with respect to age. For that matter, Choi included traditional full-time students in an analysis using the same model in an article in 2021. Concerning the validation of the relationships between the categories in the model, the results obtained validate the theorized indirect effect of the learner factors on persistence and the direct effect of internal and external factors (or at least certain factors) on persistence. Regarding academic performance (GPA), the results are more nuanced. The findings of this study did not demonstrate an impact of internal or external factors on this category. Furthermore, the investigation revealed no significant influence of GPA on persistence. This suggests that academic performance, measured by GPA, may not be a significant factor in examining persistence within the context of a single course. However, its relevance may become apparent when considering the broader context of a program of study.

Finally, our results suggest two possible additions to Choi's model. First, the direct and significant effect of learner autonomy on persistence suggests that learner factors can have a direct effect on persistence, and the model should illustrate this relationship by adding an arrow connecting this category to the predicted variable. Secondly, the results indicated the potential relationship between two factors within the same category (e.g., CoI on satisfaction), at least within internal factors. This finding suggests illustrating these interactions on the model (i.e. relationship between factors within internal factors). Alternatively, the effect of CoI on satisfaction could be interpreted as evidence that satisfaction should be regarded as an intermediate outcome, comparable to academic performance, as proposed by Choi (2021). Further investigation is necessary to verify this assumption.

Limitations and Suggestions for Future Research

It is essential to exercise caution when generalizing from the findings of this study. Firstly, the present study was conducted in two French-speaking institutions located in a Canadian region where French is the predominant language. The influence of cultural factors within this homogeneous population is a potential area of concern. Secondly, this study examined student persistence in a short-term context (i.e., in a course). The findings obtained may not be applicable—to the full extent, or at all—in instances of examining persistence in a program of studies. Thirdly, the limited variance explained for blended courses ($R^2 = 9.3\%$) indicates a need for further research to ascertain the applicability of this model in this context. Also, this study tested a limited proportion of the variables in Choi's model, and overlooking the assessment of certain associations within the category. Consequently, to establish a more robust model and provide more empirical evidence to validate Choi's model, it is imperative that other researchers direct their attention to additional variables and examine all the theoretical relations between categories, including the one proposed in this study. Finally, the elimination of three elements from the CoI scale gives rise to concerns regarding the scale's content validity. It is conceivable that the scale may no longer accurately reflect the concept. This is particularly relevant in the present study, as the items in question have all been designed to measure a dimension of PS entitled *affective expression*. Consequently, the CoI scale employed in this study did not accurately reflect all aspects of PS. Further research may be conducted on the conceptualisation of items of PS since this is also advocated by other authors (Dempsey & Zhang, 2019).

Declarations

Ethics Approval

The present study obtained ethical approval (UL-2020–020 and CER-ESS 2019–2308) from the two universities where the data were collected.

Conflict of Interest

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

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Online Strategies Instructors Employ to Support and Enhance Student Engagement and Learning in Higher Education

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Abstract
Over the past decade, evidence indicates more higher education (HE) students attracted to studying online. Important publications on this topic illustrate teachers' and instructors' growing awareness of the key conditions, elements, and dimensions that increase the likelihood of online student engagement and its impact on student learning and success. However, while studies are starting to emerge that address the online engagement strategies instructors employ and the impact of these practices, there is still a paucity of research that explores the most popular practices employed to support student engagement in HE online learning environments. Drawing on international survey data (N = 115), this study reports on insights from online instructors and learning designers regarding their preferred online engagement practices. Insights from the study provide a practice-informed account of how engagement is operationalised in online learning environments at scale. Rather than evaluating the effectiveness of individual strategies, the study maps dominant patterns of use and identifies three overarching pedagogical approaches—collaborative, cognitive, and humanising practices—that instructors most frequently employed. Importantly, the findings demonstrate that engagement strategies are rarely implemented in isolation; instead, instructors design activities that simultaneously support multiple dimensions of engagement. This paper advances knowledge in online and blended learning by documenting which student engagement strategies are most enacted by online teachers, and how these engagement strategies function collectively in contemporary higher education practice.

Keywords: Higher education, university, online teaching, online engagement, pedagogy, student engagement

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In recent years, the appetite for online learning in higher education has increased significantly. Indeed, many higher education institutions that had been reluctant to consider online delivery have now embraced online learning as a means of broadening their market share. As Stone (2022) notes, it was not until 2020 that online learning was a routine offering "by all Australian universities" (p. 139). Indeed, authors of the *Australian University Accord – Final Report* (Australian Government, 2024), state, that in order to meet "Australia's current and future skills need, a much higher share of the population will require tertiary education qualifications" (p. 44). They further articulate that:

> revised curricula and teaching methods are needed to meet the future skills needs of a knowledge economy. And advances in pedagogy are required to fulfil the potential of high-quality online and hybrid learning modes, as well as deliver teaching which supports more diverse student cohorts. (p. 61)

Online learning has become an attractive learning mode for many students. A higher proportion of mature-age students and non-traditional students, such as Aboriginal and Torres Strait Islander (First Nation) students, are seeking to study online, as well as those with a disability; from low socioeconomic backgrounds (Stone, 2016; Stone & O'Shea, 2019); students who are first in family (Stone & O'Shea, 2019); or students situated in regional, rural, and remote settings (Ragusa & Crampton, 2018). Accessibility of digital learning, along with greater flexibility and manageability, have been identified as key factors for the attractiveness of this mode of learning (Brown, 2024; Stone, 2022).

Engaged online students are more highly motivated and have an increased sense of connection and belongingness with their fellow students, tutors, and the institution (Brown, 2024; Farrell & Brunton, 2020; Martin & Bolliger, 2018). At the same time, online students are twice as likely to drop out or withdraw from university than on campus students are to drop out (Australian Government Department of Education, 2020; Li & Carroll, 2020). Significant research also reinforces the notion that online learners need to be kept engaged within the online environment, as lack of engagement can negatively impact self-efficacy, the likelihood of success, degree completion, and a sense of satisfaction (Kahu et al., 2020; Tight, 2020).

Therefore, to advance pedagogies to fulfil the potential of high-quality online and hybrid learning modes, as well as deliver teaching "which supports more diverse student cohorts" (Australian Government, 2024, p. 61), there is a need to commit to integrating online engagement strategies into teaching and learning practice (Lawrence et al., 2024; Bolliger & Martin, 2018; Martin et al., 2021). Turk et al. (2024) state for example that "engagement strategies play a crucial role in ensuring engaged and high-quality online learning experiences" (p. 1). Increasingly, instructors and learning designers are leveraging insights from theory and the significant body of scholarship research (Murphy et al., 2023), to inform their practice, and to reflect on (Redmond et al., 2022), and refine their online pedagogical practice, in efforts to increase the likelihood of student online engagement and learning.

Key theory and research have helped inform practice related to the conditions (Lawrence et al., 2024), and dimensions of online engagement (Bergdahl & Hietajärvi, 2022). Of these, aspects such as behavioural, cognitive, and affective/emotional engagement have been written about widely (Chen et al., 2018; Fredricks et al., 2016; Kahn et al., 2017; Sherifi et al., 2023). Additional significant contributions to inform practice are models of student

engagement or disengagement, including those by Bergdahl (2022), Wang et al. (2019a, 2019b), and Bergdahl and Hietajärvi (2022).

Also worth noting is the frequently referenced Garrison, Anderson, and Archer's (2000) Community of Inquiry model, which is often used to aid learning designers and instructors. This framework has been used to build communities, create a sense of belonging, and develop student relationships. Garrison et al. (2000) argue that online learning should address three major components — cognitive presence, social presence, and teaching presence.

Likewise, Redmond et al. (2018) introduced an online engagement framework that drew from categories and key themes from the broader literature and introduced five key elements of engagement: social, cognitive, behavioural, collaborative, and emotional engagement. Brown et al. (2023), in their consideration of the key insights of educators pivoting to online education, noted the "types of activities being used by educators were consistent with key elements of the Online Engagement Framework" (p. 12), with one educator stating, "the framework was helpful because it gave "something really concrete that they can do in their practice." In particular, "some of these things don't need our explicit attention in face-to-face situations, but the structure is useful when moving to online teaching" (p. 6).

It is evident, therefore, that significant research into the scholarship of online teaching and online student engagement is emerging. This research includes pedagogical approaches and strategies instructors use, and the effectiveness of these strategies in supporting online student engagement (Heilporn et al., 2021; Shi et al., 2023). Numerous studies have keenly shared a range of online engagement strategies employed during and post-pandemic (Xu et al., 2023).

However, while the literature includes a growing body of empirical work identifying strategies that promote engagement in online higher education (e.g., Martin & Bolliger, 2018; Heilporn et al., 2021; Shi et al., 2023), much of this research focuses on the effectiveness of individual strategies or is grounded in specific disciplinary or institutional contexts. As a result, there remains limited evidence regarding which engagement strategies are employed by instructors and learning designers across higher education settings and how these strategies align with multidimensional engagement frameworks. Identifying the prevalence of engagement strategies is important for understanding contemporary online teaching practice, informing professional development, and strengthening the alignment between conceptual engagement models and the practical realities of online course design.

The purpose of this study was to identify and describe the engagement strategies most frequently reported by online instructors and learning designers and to examine how these strategies align with key engagement dimensions outlined in the Online Engagement Framework (Redmond et al., 2018). The authors sought to explore: "What pedagogical practices and strategies are being used by higher education instructors and learning designers to promote student online engagement and learning?" Initially, this paper will document the existing research associated with online pedagogical strategies and innovative teaching and learning approaches that support student engagement in higher education. Throughout this paper, the term "strategies" will be used when referring to pedagogical approaches, teaching interventions, or strategies employed to support and enhance online student learning and

engagement. Next, the paper will outline the methodological details employed for the study, before addressing the key findings and insights.

Literature Review

Although student enrolments in higher education have fluctuated "in recent years due to instability caused by the pandemic" (Australian Government, 2023, p. 1), online learning has continued to grow. With this growth, many instructors are continuing to explore a range of strategies to support student engagement and learning that are, in many instances, different from the traditional teaching and face-to-face pedagogical situations. In this section we first very briefly consider research into online teaching and learning from the late 1990s to the early 2000s. Attention then turns to current research into online learning and teaching (2022-present) which highlights strategies to increase student participation and to humanise teaching and learning. The section concludes with recognition of the need to examine strategies for engaging students in learning in the online environment.

Research related to online and blended teaching and learning has occurred internationally since the late 1990s (Redmond, 2011; Lock & Redmond, 2006; Garrison et al., 2000; Salmon, 2003; Soo & Bonk, 1998; Swan, 2005; Young, 2002). One focus in the literature has been efforts to measure the effectiveness of online learning teaching and strategies (Oliver, 2001; Shea et al., 2001). This previous research provides a strong case for current researchers to reflect on, particularly in terms of key topics explored, lessons learnt, and key insights gained. One of these key insights has been the direct link between student engagement and predictors of learning and personal development, including critical thinking, problem solving, collaborative work, and communication skills (Carini et al., 2006; Griffin & Howard, 2017; Zhao & Kuh, 2004).

Empirical Research in Online Engagement Strategies

A growing body of empirical research has moved beyond conceptual definitions of engagement to examine specific strategies instructors use to foster engagement in online learning environments. For example, Martin and Bolliger (2018) identified several engagement practices perceived by students as particularly valuable, including instructor facilitation, discussion-based activities, timely communication, and opportunities for collaboration. Likewise, Heilporn et al. (2021) examined teaching strategies used to promote engagement in blended higher education contexts, emphasising intentional instructional design and structured interaction to support participation and persistence. More recently, Shi et al. (2023) synthesised evidence regarding instructional strategies for engaging online learners, noting the importance of learner-centred approaches, active learning, and modality-sensitive teaching strategies. Similarly, studies focusing on online collaborative learning have highlighted the effectiveness of structured peer interaction and discussion technologies such as wikis and discussion forums in promoting engagement and deeper learning (Ioannou et al., 2015; Oyarzun & Martin, 2023).

Collectively, this body of scholarship illustrates that engagement strategies in online learning are well documented, and that instructor-led interventions such as collaborative activities, structured discussion prompts, metacognitive questioning, and instructor presence are strongly associated with positive student learning experiences and participation (Bolliger & Martin, 2018; Hamadi et al., 2023). However, while many studies have examined strategies in specific course contexts, fewer studies have explored which engagement strategies are most commonly used across teachers and institutional settings, or how

instructors intentionally combine strategies to support multiple dimensions of engagement simultaneously. Addressing this issue is important because engagement strategies are often implemented as interconnected pedagogical practices rather than discrete interventions.

Recent research on online student engagement provides insight into ways to positively increase student participation and learning outcomes, such as establishing instructor presence, viewing and supporting engagement in multidimensional ways (often by employing innovative pedagogical strategies, or a different technological tools), and structuring course content with clarity and accessibility. For example, researchers such as Hollister et al. (2022) found students in asynchronous online courses reported higher satisfaction and perceived learning when a greater portion of their grade was based on discussions, suggesting incorporating interactive elements enhance engagement. Bedi (2023) argues that student motivation to learn and student self-efficacy are positively associated with engagement, with self-efficacy helping to mediate the relationship between motivation and engagement, highlighting the importance of fostering students' confidence in their abilities. Online engagement can also be boosted through measures such as optimising class organisation, providing timely feedback, harnessing course learning analytics, and fostering a sense of community among students (Mowreader, 2023). This research additionally highlights the advantages of embedding advanced technologies, experiential learning, and sustainability into curricula.

Largely emanating from the United States are strategies emerging from "humanising teaching" (Foote, 2023; Mapaling & Hoelson, 2022). Research here involves conscious strategies to cultivate personal connections, empathy, and a sense of community between teachers and students (Latecka, 2023; Mapaling & Hoelson, 2022; Sathorar et al., 2023), thereby enhancing engagement and learning outcomes. Recent research (Foote, 2023) also indicates that humanising teaching can mitigate the often-impersonal nature of online learning environments by emphasising teacher presence, personalised communication, and the inclusion of students' diverse backgrounds and experiences.

Strategies for creating human connection with and among learners contribute to interactions beyond content delivery, including authentic engagement and support (Devis-Rozental & Clarke, 2020; Mapaling & Hoelson, 2022); embedding opportunities to foreground students' backgrounds, cultures, and life experiences (Lawrence et al., 2024), as well as nurturing learning contexts where power is shared between students and teachers. Kim et al. (2023) maintain incorporating various modes of communication, such as videos and social media, caters for diverse students learning needs, provides opportunities for engagement, and fosters a sense of community (Stewart, 2024). Foote (2023) brings these humanising strategies together by emphasising: (1) the need to understand ourselves and our students; and (2) implementing strategies to create inclusive and responsive learning environments.

Existing scholarship demonstrates that online engagement is multidimensional and teachers can foster engagement through a range of intentional pedagogical strategies, including collaborative learning activities, structured discussion facilitation, feedback practices, and humanising approaches. At the same time, the literature suggests that strategies are often examined individually or in small-scale studies, making it difficult to determine which practices are most common across higher education contexts. Therefore, further research is warranted to document teachers' reported engagement practices at scale and to explore how these strategies align with engagement frameworks.

Conceptual Framework

This paper investigates the use of specific strategies that higher education instructors use to promote student online engagement. The study is informed by the Online Engagement Framework (Redmond et al., 2018), which conceptualises engagement as a multidimensional construct comprised of five interrelated elements: social, cognitive, behavioural, collaborative, and emotional engagement (See Table 1). The framework was developed from synthesis of student engagement literature and was designed to support instructors and learning designers in identifying strategies and learning activities that strengthen engagement in online higher education contexts. The Online Engagement Framework is conceptually aligned with other widely used online learning frameworks such as the Community of Inquiry model (Garrison et al., 2000), which highlights the importance of teaching, social, and cognitive presence. However, the Online Engagement Framework extends these perspectives by offering a broader typology of engagement elements and by explicitly identifying indicators and pedagogical strategies that can be operationalised in online learning design and teaching practice (Redmond et al., 2018).

Social engagement refers to the development of meaningful relationships between learners and instructors that foster connection, belonging, and trust. Social engagement strategies commonly include icebreaker activities, introductory videos, informal discussion forums, and opportunities for students to share personal and professional experiences. Cognitive engagement refers to the mental effort learners invest in understanding, synthesising, and applying course content (Brown et al., 2023). Strategies that foster cognitive engagement include reflective activities, scaffolded discussion prompts, problem-solving tasks, structured questioning, and opportunities for metacognition, such as asking students to justify decisions or connect theory to practice. Behavioural engagement refers to students' active participation in learning tasks and their development of academic and professional learning behaviours. Behavioural engagement may be supported through explicit modelling of expected participation norms, clear assessment guidance, structured weekly learning routines, and instructor feedback that reinforces persistence and academic skill development. Collaborative engagement refers to students learning with and from peers and developing professional connections and networks. Collaborative engagement strategies often include group assessment tasks, peer feedback processes, breakout room discussions, peer mentoring activities, and structured teamwork activities that promote shared responsibility and cooperative learning (Brown et al., 2023). Emotional engagement refers to students' affective connection to learning, including motivation, confidence, and persistence. Strategies supporting emotional engagement include instructor encouragement, timely and supportive communication, opportunities for student choice and flexibility, and practices that foster psychological safety, such as check-ins, polls, and activities that normalise uncertainty and challenge.

Table 1

Online Engagement Framework for Higher Education

Online Engagement Element	Example (Illustrative Only)
Social	Building community Creating a sense of belonging Developing relationships Establishing trust

Cognitive	Thinking critically
	Activating metacognition
	Integrating ideas
	Justifying decisions
	Developing deep discipline understandings
	Distributing expertise
Behavioral	Developing academic skills
	Identifying opportunities and challenges
	Developing multidisciplinary skills
	Developing agency
	Upholding online learning norms
	Supporting and encouraging peers
Collaborative	Learning with peers
	Relating to faculty members
	Connecting to institutional opportunities
	Developing professional networks
Emotional	Managing expectations
	Articulating assumptions
	Recognising motivations
	Committing to learning

From *Redmond et al., 2018*

Methodology

The research described in this paper consisted of four phases: i) obtaining ethical clearance; ii) promoting the survey; iii) recruiting participants; and iv) analysing the data.

Ethics

Ethics approval was obtained through the university human ethics committee (H21REA102). Researchers provided participants with clear information about the anonymous and voluntary nature of the survey. Submitting a fully or partially completed the survey was taken as consent. Due to the anonymous nature of the survey, participants could not withdraw from the study after submitting their response. Participants, however, did not need to answer every question.

Research Design

An anonymous survey consisting of a closed- and open-ended questions was chosen to answer the research question. Because the purpose of this study was to identify and describe the engagement strategies most commonly employed by online instructors and learning designers, a survey approach was appropriate. Survey methods have been widely used in scholarship of teaching and learning research to document patterns of instructional practice across broad participant groups (Divan et al., 2017; Wolf et al., 2016). Surveys are particularly effective in targeting—and having maximum reach for—a broad national and international group of professionals who work in higher education (Wolf et al., 2016). This reach is beneficial where the focus is revealing and gaining insights into the strategies that respondents adopted to promote and facilitate online student engagement and learning in higher education. This approach supported the present study's aim of capturing strategies used across diverse disciplines and institutional contexts, rather than evaluating a single intervention within one course or program.

Participants

To avoid a low response rate numerous strategies were used to gain data. As a key focus of the online survey was seeking examples of the different ways participants supported online engagement in their teaching, including strategies linked to the elements of online student engagement, one recruitment strategy was to email all authors who had previously cited a paper written by several of the researchers of the study reported here that referred to an Online Engagement Framework (Redmond et al., 2018) (n=320 emails). This paper had gained significant traction, especially during the world pandemic when many higher education institutions were pivoting online as the paper offered accessible ways to understand and refer to different types (elements) of online engagement. Google Scholar was used to retrieve details of all publications where the seminal paper written by several of the authors of this paper had been cited (with more than 184 citations identified at the time data was being retrieved for the study). The survey was then sent to authors of these papers. The survey was also promoted through social media such as Facebook groups and Twitter. Additionally, researchers promoted the survey to their colleagues, professional contacts, networks (LinkedIn), and organisations.

A limitation of the research was the lack of verification of identity of the respondents; however, this issue is the same with all anonymous surveys. The goal was to gain an international response to enhance generalisability. There was a focus on recruiting academics, learning designers, and researchers in higher education with an interest in online engagement and who used online engagement strategies in their work. Australian and international participants completed the survey. There were 172 responses to the survey. Fifty-seven participants fully completed the survey and 115 participants partially completed the survey.

The data reported derives from the fully completed surveys. From the 57 completed surveys, 20 participants were Australian, 30 were international, and seven indicated "other." International participants were from Canada, New Zealand, Philippines, Scotland, the United States, and Taiwan. Thirty-five respondents were academics. The majority of participants (24) identified their discipline as Education. Participants were also from Business, Humanities, Allied Health, Health, Sciences, and Information Technology disciplines. All participants were highly experienced online teachers, with 25 having taught online for more than a decade. More than half of the participants responded to "using" or referring to the Online Engagement Framework.

Instrument and Data Collection

The survey contained 21 questions grouped into five sections. First, respondents were asked four demographic questions (place of work — Australia/International, role in higher education, discipline, length of time teaching online). Second, they were asked four questions about their awareness of the Online Engagement Framework (Redmond et al., 2018) and whether it had influenced their practice. The final three groups of questions centered on respondents sharing examples of their online engagement practices. Third, respondents were asked two questions about engagement indicators. Fourth, they were asked five questions about teaching and learning activities based on the Online Engagement Framework. For example, they were asked "Please add relevant examples of activities that demonstrate the indicators of cognitive engagement," with illustrative examples offered in the question as guidance. Fifth, six open-ended questions were posed. These questions included:

- "Do you have additional thoughts that you have found effective in designing and delivering your online courses that do not correspond to any of the online

engagement indicators in the current framework? No Yes (Please provide examples)."

- "Are there other student engagement aspects that you feel are important but are not represented in the existing framework? Yes (Please provide examples) No."
- "What other suggestions do you have for improving the existing framework?"
- "What resources (academic sources, colleagues, equipment available in your location, etc.) informed what you did in relation to each engagement indicator?"

It was anticipated that the survey would take approximately 10-15 minutes. The survey was hosted on the Lime Survey platform and was open for 60 days.

Data Analysis

After the completion of the survey, a thorough analysis was undertaken. Thematic content analysis (Delve et al., 2023; Park et al., 2017) was used in this study. Initially, a researcher, aided by NVivo, used inductive coding to identify key words emerging from the data (Braun & Clarke, 2006). These keywords included: "group,", "discussion," "forum," "peer," "questions," "reading," and "videos." Three researchers further analysed these codes, developing themes from the keywords. Researchers used a large Miles and Huberman (1994) style data grid that included columns for themes and supporting evidence (quotes) per theme for further analysis. This analysis showed a rich understanding of the meanings that online educators bring to learning situations for the benefit of student engagement and learning. Quotes to demonstrate each theme were selected, and the number of responses in each category counted, as a form of summative content analysis, to provide an estimate of category usage across the group (Hsieh & Shannon, 2005).

The Online Engagement Framework's (Redmond et al., 2018), five elements (behavioural, cognitive, emotional, social, and collaborative engagement), were used in this research to position the research as a conceptual informing framework, rather than as a coding schema. Our intent was not to test or validate the framework, but to explore how online teachers describe and prioritise engagement strategies in their own terms.

The analysis began with inductive coding of open-ended survey responses to capture participants' language and descriptions of practice without constraining them to predetermined categories. This approach was aligned with the exploratory nature of the research question, which sought to identify *what practices are being used* rather than *how well practices map to an existing framework.*

Relationship Between the Framework and Emergent Themes

While the final themes were inductively derived, the Online Engagement Framework informed the study in the following important ways: It guided the design of the survey instrument, including the structure and wording of questions related to engagement practices, and it provided a theoretical lens through which the findings were discussed, particularly in recognising the multidimensional and overlapping nature of engagement.

The most frequent words or terms used by participants, within their explanations and reference to interventions to support online student engagement that emerged from initial coding, were discussion/forums (n=46) (which encompassed interventions that referred to

online discussion forums, discussion activities, and discussion boards); group (43) (e.g., partnering in groups, online group assignments, facilitating group work); peer (26) (e.g., students get to meet peers; feedback from assessment, encouraging peer interactivity); and questions (26) (e.g., via polls and questions, tutorial questions, and open-ended questions). Other popular keywords or themes from online educator interventions were reading/literature review (15) (e.g., deeper readings, reading task, academic/research literature); video (14) (e.g., watching videos, instructor created videos; providing introductory videos) and encouraging/coaching (13) (e.g., encourage debate, coaching for sincerity). More detail is provided in Table 2.

Table 2

Initial Coding for Key Themes of Online Instructor Interventions

Intervention	Number	Examples of Keyword Inclusions
Discussion Forums	46	Discussion forums Discussion activities Discussion boards
Group Engagement	43	Partnering in groups Online group assignments Facilitating group work
Peer Engagement	26	Students get to meet peers Encouraging peer interactivity Peer feedback
Questions	26	Via polls and questions Using tutorial questions Open-ended questions
Asking questions	26	Asking questions Problem solving Analysing a problem and what is asked
Reading literature	15	Further deeper readings Reading task before a lesson Academic/Research Literature
Video	14	Watching videos Instructor created videos Providing intro videos
Encouraging and Coaching	13	Encourage students to highlight their concerns Encourage debate Coaching for sincerity
Problem	12	Connecting problems with potential solutions Analysing a problem Giving students a problem to solve
Modelling	11	Modelling a “not yet” mindset Model empathy Important for academic to model the correct behaviour to students
Break out	11	Meet peers in speed breakout rooms Breakout rooms in zoom Breakout rooms for students to socialise and connect

		Play in teams (Lego)
Teamwork	9	Team teaching
		Team based effort
		Reflection quizzes
Quiz	5	Teacher paced cell phone delivered quiz
		Quizzes
Guest lecture	2	Guest lecture session

Limitations

Before presenting the research findings, it needs to be recognised there were several limitations with this study. Of the 172 responses received, 115 were partially complete and 57 were fully complete. While recognising that the time to complete the survey could have been a deterrent for busy academics, it is also possible that those with most interest and knowledge in enhancing the engagement of students learning online responded to the survey. While anonymity limited information about participants, it aided participants' completing the survey and providing full responses to questions.

Findings

The study sought to explore the strategies adopted by instructors in promoting and facilitating student engagement and learning in online learning environments. Study participants were teaching different courses, across different levels, and across different disciplines, geographies, and institutional types. However, qualitative analysis of participants' responses revealed consistency in several of engagement examples: collaborative teaching and learning; cognitive teaching and learning; and humanising teaching and learning, related to purposeful support, teacher presence, and the affordance of individual choice. These categories emerged from the second phase of analysis and after lengthy discussion and critical reflection by the research team. Researchers noted the original themes, rather than being disparate, were subsumed, related, and referred to overarching pedagogical strategies, or teaching and learning approaches. Respondent quotes are presented in italics.

Collaborative Teaching and Learning

A sizeable number of interventions and engagement activities sat within this category (134). Engagement strategies referred to in this category were activities such as break-out groups, group work, or peer-related (80) practices that yielded the highest results, as well as activities such as teamwork (n=9) and discussion/forums (46). Table 3 highlights the second-level coding and the number of associated interventions that aligned with collaborative teaching and learning. These interventions were about students "working with others, including discipline peers, educators, and university and industry-wide personnel," sharing ideas and communicating effectively, which would "serve them well in their learning, personal and professional lives" (Author et al., 2023, p. 45).

Results from the study reflect instructors identifying that social interaction among online students was imperative to learning (Vygotsky, 1978). Therefore, they sought out pedagogical strategies supporting this type of learning, while at the same time promoting cooperation and assisting students to build and nurture broader connections across the student cohort, as well as with teaching staff (Oyarzun & Martin, 2023). While the appreciation of collaborative learning is consistent with those identified in traditional face-to-face learning

strategies (Scager et al., 2016), it appears that collaborative engagement strategies were particularly valued for online learning as this approach assisted students in establishing a sense of belonging and connectedness to other students, instructors, and the university (Chatterjee & Correia, 2020; Eden et al., 2024; Martin & Bolliger, 2018). These strategies helped mitigate isolation, which can be common in online education.

Table 3

Breakdown of Collaborative Teaching and Learning Examples and Sub-Categories

New Categories	Old Categories / Interventions	Total Count	Sub-category Count
Collaborative learning	Break out / Group / Peer	134	80
	Teamwork		9
	Discussion / Forum		46

Peer Activities

Instructors reported widespread use of what they referred to as "peer activities" (Break-out opportunities/Group/Teamwork/Peer feedback/Speed Meet") as an essential aspect of their teaching to engage and aid learning. "Peer activities" were often mediated via discussion boards within the Learning Management System (LMS) or via breakout rooms in online tutorials. Examples included putting "students into small groups to aid one another in their study," to "try out answers with positive support," and to encourage "peer feedback" from students "sharing their thoughts on key topics." This use reflects a widely used asynchronous learning tool in online and blended courses. Such tools were to support student-student interaction and to provide opportunities for group assessment (Kipling et al., 2023).

Reference to group support, teamwork, and break-out opportunities included connecting students of similar contexts (including equity groups) and organising informal "chat groups" for building a strong sense of belonging. There was frequent reference to online "groups." Some participants identified online group assessment tasks, such as group presentations, project work, and peer/group conferences. These activities reflected the instructors' valuing of students learning from and with others, including strategies related to peer learning, and peers providing constructive feedback as part of peer assessment, or as part of a more informal process of encouraging peer interactivity in online learning. The following example captures these types of interventions:

> I trialled a research proposal presentation where MA students and PhD students could provide their ideas and thoughts on a peer's research ideas. It is one way to learn informally outside of their usual formal course activities.

Another participant noted, "I use peer feedback from students to encourage debate and the justification of the stance taken by the proposing student."

Further participants used breakout rooms for a range of group or peer support purposes. One example shared was "Speed Meet" at the start of the semester, described as "a

fun rotating Zoom session where students get to meet peers in speed breakout rooms." Breakout rooms during Zoom tutorials were also a valued strategy, particularly for encouraging smaller group discussion activities, noted by participants.

Discussion Forums

The popularity of collaborative learning reflected in the survey findings indicated the importance placed on activities that directly involved engagement among students. This type of strategy largely referred to the benefits of group work or students sharing their learning and thoughts with their peers. A central strategy that instructors used to support collaborative online learning and engagement, which is not unexpected, was online discussion and the use of forums (46 mentions). This finding supports existing research that reflects "connections with peers," particularly in online learning, as a critical aspect of pedagogical approaches employed by instructors, with wikis and discussion boards being two of the most common technologies adopted (Oyarzun & Martin, 2023; Ioannou et al., 2015; Peddibhotla & Jani, 2019; Yang, 2024). Participants spoke of using wikis or discussion forums for a range of purposes, with the common underpinning focus on students connecting with their peers as well as the course facilitation team. Forums were regularly referred to including "Forums asking for student contributions. Also, students choosing special areas and then sharing their knowledge with the rest of the group." Instructors also spoke of the need to extend a collaborative approach in "group projects" ("group assessments" and also scenarios in which "students work in groups to develop strategies to solve)."

Alongside, but at times separate from the use of forums was the use of both formal and informal discussion opportunities, such as *drop-in sessions* for actively stimulating learning and engagement. Informal drop-in sessions held via Zoom were seen as valued opportunities for students to build relationships and connections with their fellow students and their instructors. These included a time for students to discuss their studies and progress, or a time to informally chat with class members about their studies or questions they may have in common.

Teamwork

Instructors frequently referred to learning activities where teamwork was required. Teamwork strategies were embraced as a pedagogical approach fostering student connectedness and engagement. One instructor outlined a learning activity they believed established high levels of student engagement and helped facilitate collaboration through creating "a team charter," along with identifying "the roles each member will take and an activity where they also decide how to deal with challenges and share their strengths." This activity involved instructors explicitly unpacking associated behavioural engagement strategies. Instructors mentioned that to support successful group activities it was important to establish clarity of specific roles, and strategies to overcoming challenges, and reinforce the importance of leveraging the strengths of team members.

Cognitive Teaching and Learning

Engaging students cognitively was the second category that emerged. This category referred to strategies and interventions such as quizzes, guest lectures, asking questions, and posing problems or problem-solving (Table 4). It is important to note that instructors referenced using other engagement strategies, such as collaborative engagement (e.g., discussion forums) to extend the cognitive aspects of students' online engagement and learning. Clustering, or combining a range of these approaches can be an effective way to move student learning along a continuum from surface level to deeper or metacognitive

learning. When students have opportunities to reflect on their learning and the relationship to existing knowledge, they are likely to experience cognitive engagement in online courses (Brown et al., 2023).

Central to this online teaching strategy associated with metacognition was the broader use of discussion forums (beyond what has been outlined in the collaborative engagement section above). This strategy helped to ensure a pedagogically nuanced approach to discussion forum usage, beyond simply engagement from a social aspect, or collaborative engagement, to engagement strategies that incorporated learning or cognitive engagement. Educators in this research outlined the need to "be active" in online learning forums as a means of addressing questions and redirecting students. This underpinning goal was captured in a range of responses including: "creating open-ended questions that invite discussion and multiple potential responses and intentionally being controversial by asking provocative questions to drive students to deeper depths of the issues under discussion." Another educator saw using discussion forums as an opportunity to further deeper thinking saying:

> I make it a point to engage with them on their discussion boards with supplemental questions on the topic that drive their thinking deeper. As a result, the discussions go into great depth and new learning. If their comments are boring or ho-hum, I will either play Devil's Advocate or ask advanced questions).

Online instructors reported using other cognitive engagement strategies which included: asking questions (26), using readings and literature (15), videos (14) modelling (11), using quizzes (5), and creating problem-based learning scenarios (12). Several educators referred to using literature and readings as a means of engagement and assisting learning. Some educators incorporated readings and relevant literature, before the lesson (lecture, forum discussion, etc.), as a reading summary (online worksheet, video, mind map, poster, etc.) or to facilitate a fishbowl activity.

Videos and personalised video clips were identified as another valuable approach for heightening cognitive engagement. A tip shared in several responses was the integration of provocation or targeted questions to consider when watching the video. Several instructors noted that a further underlying reason or benefit of personalised videos was to help build "strong connections" and online "teacher presence." Other instructors linked personalised videos with discussion board activities. The following example captures this point: "I use my own personalized videos to give feedback on the discussion boards and encourage students to do the same.. Finally, one instructor used video to provide feedback to students in a personalised manner so students feel more engaged and connected to the instructor, stating they use videos for "honest feedback to students using video so they can see my face, hear my voice and sincerity."

Quizzing methods were used by a small number (5) of participants in this study, despite it being a commonly used means for online students and instructors to get a sense of the understanding of the content and as a means of engaging students (Evans et al., 2021; Ross et al., 2018). In the few instances of quiz use mentioned by instructors, the common theme was affording students opportunities to reflect on recent learning. As anticipated, online instructors—perhaps like classroom teachers—referred to problem-solving (12) as a means of deepening students' understanding of a topic and facilitating engagement. Instructors in this research spoke of using problem-solving activities with student activities designed around "the analysis of a problem," "through asking students to connect with

potential solutions," and by "encouraging students to explain and evidence critical thinking in identifying problem solutions and/or critical decisions." Often online instructors used group work activities and problem-solving learning together, as one educator explains that she likes to give "students a problem to solve in pairs and report back to class."

Table 4

Examples of Cognitive Teaching and Learning Strategies in the Data and the Number of References for Each Strategy

Example	Number of References
Asking questions	26
Reading/literature	15
Video	14
Problem	12
Modelling	11
Quiz	5

Humanising (Peer or Instructor Support)

The third category identified was "Humanising," which included both instructor and peer support and/or practices related to "humanising" the learning experience for students. Humanising in this research was associated with instructor presence, peer activities, and increased student agency (Li et al., 2022). Important to note is that instances of support by instructors often overlapped with other strategies and, as such, only 13 exclusive instances of humanising were identified. In each of these instances, there was often mention that "*instructors were the key,"* "*providing prompt and appropriate responses,*" and "*providing intro videos each week with personalised messages to students*." Therefore, it needs to be acknowledged here that support and humanising were indeed embedded within the categories identified above, particularly those such as break-out groups, group work, peer, teamwork, discussion forums, questions, asking questions, encouraging and coaching, problem and modelling. Such embeddedness of student engagement practices is related to the interconnectedness, or multidimensional nature of online engagement, with many overlapping behaviours, practices, and strategies (Brown et al., 2023).

Although fewer participants identified support from both peers and the instructor, the importance of the data gathered with this category does indeed outline the significance of student engagement benefitting from humanising the learning experience through encouragement and coaching. Examples of this engagement practice included:

> I hold open Zoom calls one night each week, on a night and at a time determined by students. There is no topic, I do not lecture, I allow the conversation between those who show up to evolve on its own.

Another example which also reflected the "choice" or "flexibility" aspect of this category was:

> Students can come in late and leave early if they need to …I believe that these sessions build relationships among students and with me and that they release some creative thinking that other venues of learning do not allow or may even discourage.

Another participant stated that they:

> ensure students are engaged and ready to learn. I do this through supportive measures. I find this encouragement supports attendance but sometimes students are busy with working and family lives, so I connect with these students individually.

Another instructor used personalised videos to provide a humanising experience for students, "to give feedback and on the discussion boards and encourage students to do the same." Finally, another participant simply stated that humanising can be managed through, "Coaching with sincerity."

Discussion

Results from the study reflect instructors identifying that social interaction among online students was imperative to learning (Brown et al., 2023; Hollister et al., 2022; Vygotsky, 1978). Therefore, they sought out pedagogical strategies supporting this type of learning, while at the same time promoting cooperation and assisting students to build and nurture broader connections across the student cohort, as well as with teaching staff (Oyarzun & Martin, 2023). While the appreciation of collaborative learning is consistent with those identified in traditional face-to-face learning strategies (Scager et al., 2016), it appears that collaborative engagement strategies were particularly valued for online learning as this approach assisted students in establishing a sense of belonging and connectedness to other students, instructors, and the university (Chatterjee & Correia, 2020; Eden et al., 2024; Martin & Bolliger, 2018). These strategies helped mitigate isolationism, which can be common in online education (Dulfer et al., 2025; Yan et al., 2024). Findings about discussion forum use supports existing research that reflects "connections with peers," particularly in online learning, as a critical aspect of pedagogical approaches employed by instructors, with wikis and discussion boards being two of the most common technologies adopted (Ioannou et al., 2015; Oyarzun & Martin, 2023; Peddibhotla & Jani, 2019; Yang, 2024).

With respect to teamwork, it may be the case that results from this study indicate that collaborative teaching and learning were embraced and valued even more as a strategy within the online environment than within traditional classrooms (Panitz & Panitz, 2018). While not direct evidence, a recent review of 63 articles and publications on online collaborative learning technologies indicated these strategies were most often embraced within a LMS (Oyarzun & Martin, 2023). Finally, many of these examples related to collaborative learning were highly connected with an intent to facilitate metacognition for students. This insight further consolidating the multidimensional and interrelated nature of online engagement elements and the associated strategies employed by instructors. As well, considering the findings about cognitive engagement, this study supports existing research (Chen & Chen, 2024) and the social constructivist theory of learning where "learners are not passive receivers of knowledge but rather participate in their respective construction of knowledge," enabling them to use their metacognitive skills (Chatterjee & Correia, 2020, p. 62).

Many of the participants in this research spoke of the connection between student engagement and learning, with instructors largely seeing student learning and student engagement as one and the same—learning aiding engagement and engagement aiding learning (Lawrence et al., 2024). Important to note was a commitment to teacher presence, along with instructors scaffolding and carefully considering their role and practice in efforts to maximise metacognitive teaching and learning, such as framing higher-order discussion questions (Bolliger & Martin, 2021). This supports existing studies that reflect the crucial role the instructor plays in research in terms of the importance of and attention to supporting metacognitive learning and engagement in higher education (Hamadi et al., 2023).

The examples of online engagement strategies associated with peer and instructor support noted earlier were about approaches related to "connectedness to others" (Gleason, 2021; Mehta & Aguilera, 2020) including peers and the online instructor, where individual choice is valued and reflected in the types of learning activities provided (Kahn, 2017). As outlined, findings from this study indicated that the most used interventions were those related to collaborative learning, followed by cognitive strategies. While few explicit references were made by online instructors to the third category of humanising, evidence of integrating the intent to "humanise" and "support" through a personalised approach to online teaching and learning was evidenced numerous times across participant responses. A key insight of these online engagement strategies employed by instructors was the frequency in which multiple types of engagement were achieved and supported through the strategies employed.

Conclusions, Implications, and Reflections

The identification of the three main strategic approaches for supporting student engagement and learning—collaborative, cognitive, and humanising practices—raises implications for online instructors, designers and university teaching policy makers, particularly in terms of the types of online activities that differ from face-to-face activities that have traditionally been used in teaching and learning. Universities often assume that all learning is the same, promoting the idea that online, face-to-face, and blended modes should duplicate the primary mode of instruction. This assumption does not allow educators to gain the advantages, or to leverage from the different types of learning environments and contexts. For example, the immediacy of face-to-face or synchronous activities provides a different experience to those completed in an asynchronous mode. Consequently, it is a fallacy that educators can simply adapt or adopt common face-to-face practices in online teaching without considering the nuances of the environment.

In addressing the research question regarding online engagement practices and strategies, it is not surprising that discussions, group work, and questioning constitute many activities designed for online courses. These same activities would occupy a large percentage of activities in traditional face-to-face classes yet are nuanced and carefully considered for the online learning environment in higher education. These interventions are instructor-led and broadly associated with teaching that occurs before or during a learning activity. A key insight to emerge from the study is that online teaching and learning strategies are not usually deployed in isolation, rather online strategies frequently address and support multiple types of student engagement, including collaborative, cognitive and collaborative engagement.

In conclusion, an implication of the move to learning online has contributed to the view that learners and instructors have become novices in this modern learning environment. All actors in the learning environment (learners, teachers, designers, and policymakers) must decide how best to use the online environment and digital devices for the best learning outcomes effectively. These considerations should not perpetuate the status quo and assume that, because learning has moved online, policymakers, students and educators know how best to use those environments because each of these actors has a different stake in the outcomes and different considerations as to the inputs. Critical in the decision-making of engagement strategies should always be a consideration for discipline knowledge and skills, expected learning outcomes, student context, pedagogical approaches and affordances of the technology or digital devices, before designing any learning space—this means the online space also.

Future research could explore contemporary benefits of online learning at scale which may be different than those experiences in the late 1990s and early 2000s when this type of research began. In addition, contemporary engagement strategies provide some hints towards activities which engage students more than others. Based on existing research on pedagogical practices that support online student engagement, it is important to recognise that instructors are critical in supporting conditions for online student engagement. We know enough about what it takes to engage students in online learning and learning environments. However, there is still the potential to better understand which of these pedagogical strategies speak directly to student learning and student engagement.

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Enhancing Deep Learning in Blended Learning Environments by Investigating the Interplay of Self-Regulated Learning, Social Presence, Cognitive Load, and Learning Outcomes Among Pre-Service Teachers

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Abstract
Blended learning has become central to higher education, yet its capacity to promote deep learning depends on how cognitive, self-regulatory, and social factors are designed across online and face-to-face components. This study examined the relationships among cognitive load, self-regulated learning (SRL), social presence, deep learning, and learning outcomes among 450 Indonesian pre-service teachers in a structured blended learning environment. Data from survey responses and course-performance indicators were analyzed using partial least squares structural equation modeling (PLS-SEM) to test direct and mediated relationships. The results showed that cognitive load positively predicted deep learning but did not directly predict learning outcomes, indicating that cognitive demands can support achievement when they stimulate meaningful processing rather than overload learners. SRL also positively predicted deep learning but had no direct effect on outcomes, suggesting that regulation strategies improve performance mainly when translated into higher-order engagement. Deep learning strongly predicted learning outcomes and mediated the effects of cognitive load and SRL on achievement. Social presence did not significantly predict deep learning and negatively predicted learning outcomes, implying that interaction may be insufficient or distracting when not pedagogically structured. These findings identify deep learning as the central mechanism linking cognitive, self-regulatory, and social factors to academic performance. The study recommends blended learning designs that optimize cognitive challenge, scaffold SRL, and structure social interaction around purposeful inquiry, feedback, and knowledge construction.

Keywords: Blended learning, deep learning, cognitive load, self-regulated learning, social presence, learning outcomes

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Blended learning is a prominent instructional approach integrating face-to-face and online learning to optimize student engagement and learning outcomes (Singh et al., 2021). In practice, blended learning is not inherently student-centered; its effectiveness depends on how instructional activities, interactions, and cognitive demands are designed across online and in-person components. Within well-designed blended environments, deep learning processes, characterized by higher-order thinking, meaningful knowledge construction, and sustained cognitive engagement play a crucial role in determining the quality of students' learning experiences (Mystakidis et al., 2021). However, achieving deep learning in blended environments remains challenging due to varying levels of self-regulated learning (SRL), social presence, and cognitive load among students (Lobos et al., 2024; Wu, 2025; S. Zhao & Cao, 2023).

Self-regulated learning (SRL) has been widely recognized as a critical determinant of academic success, particularly in online and blended learning settings where students must independently manage their learning processes (ElSayad, 2024; Jiang et al., 2022; Li et al., 2024). Effective self-regulated learners engage in goal setting, self-monitoring, and self-reflection, which facilitates deep cognitive engagement and improves learning outcomes (Rui et al., 2024; Russell et al., 2022). Nevertheless, many university students, particularly in systems shaped by teacher-centered instructional traditions, struggle to sustain effective self-regulation in blended environments, resulting in inconsistent engagement and uneven learning outcomes.

Another key factor influencing deep learning in blended environments is social presence, a construct with a long and well-established history in educational technology research. Social presence was initially introduced in Social Presence Theory by Short et al. (1976) to explain how individuals perceive others as "real" in mediated communication. The construct was later incorporated into the Community of Inquiry (CoI) framework (Akyol & Garrison, 2008; Garrison et al., 1999), where social presence is conceptualized as a foundational element that supports both cognitive and teaching presence in online and blended learning environments. In the present study, social presence refers to the extent to which students perceive their peers and instructors as real, authentic, and accessible in online interactions (Ratan et al., 2022; Turk et al., 2022; Wut & Xu, 2021). High levels of social presence have been linked to a sense of belonging, increased motivation, and opportunities for collaborative discourse that can support deep learning (Mystakidis et al., 2021). However, social presence alone does not guarantee meaningful learning, as unstructured or poorly guided peer interactions may fail to promote higher-order thinking or shared regulation of learning (Heilporn et al., 2021). Prior research suggests that social presence contributes to learning outcomes most effectively when collaborative interactions are purposefully designed and cognitively oriented (Miao & Ma, 2022).

Cognitive load theory (Sweller, 2011) offers an additional perspective for understanding learning processes in blended environments. Cognitive load refers to the mental effort required to process information and is commonly distinguished into intrinsic load (task complexity), extraneous load (ineffective instructional design), and germane load (cognitive resources devoted to schema construction) (Kirschner, 2002). Rather than viewing cognitive load solely as a barrier to learning, contemporary perspectives emphasize that well-managed cognitive challenge,

particularly germane load, can support deeper cognitive processing and conceptual understanding. In blended learning contexts, where students must navigate multiple formats, tools, and interactional demands, instructional designs that minimize extraneous load while supporting productive cognitive effort are essential for fostering deep learning (Müller & Wulf, 2024). Conversely, poorly designed tasks or limited self-regulatory capacity may result in cognitive overload that undermines meaningful engagement (Longo, 2022).

Although previous studies have examined self-regulated learning, social presence, and cognitive load as individual predictors of learning in online or blended environments, limited empirical research has investigated how these factors interact as an integrated system to shape deep learning and learning outcomes, particularly in non-Western higher education contexts. This gap is especially relevant for pre-service teachers, whose learning experiences not only affect their own academic development but also influence how they will design future learning environments for their students.

Therefore, this study investigates the structural relationships among self-regulated learning, social presence, cognitive load, deep learning, and learning outcomes in a blended learning environment among pre-service teachers in Indonesia. By examining both direct and indirect relationships, the study aims to clarify the mediating role of deep learning and to generate empirically grounded insights that can inform the design of cognitively engaging, socially structured, and pedagogically effective blended learning environments.

Literature Review

Blended learning has become a prominent instructional approach in higher education by integrating face-to-face instruction with online learning activities, thereby offering flexibility, accessibility, and opportunities for richer learning experiences. This modality has been widely adopted due to its potential to support deep learning, which involves higher-order thinking, the construction of meaningful knowledge, critical reflection, and long-term retention (Shi & Lan, 2024; Wu, 2025). However, evidence suggests that simply combining online and face-to-face components does not automatically result in deep learning. Instead, the quality of learning in blended environments is shaped by complex interactions among cognitive, behavioral, and social factors, particularly self-regulated learning (SRL), social presence, and cognitive load. Understanding how these factors operate as an interconnected system is especially important in teacher education programs, where pre-service teachers must not only master content knowledge but also develop pedagogical competencies that they will later transfer into their own instructional practices.

Self-regulated learning has consistently been identified as a key determinant of academic success in online and blended learning contexts, where learners are required to manage their learning processes with greater autonomy (Jansen, 2021; Onah et al., 2022; Vargas-Mendoza & Gallardo, 2023). SRL encompasses goal setting, strategic planning, self-monitoring, effort regulation, and reflective evaluation, all of which support sustained engagement and adaptive learning behaviors. In blended learning environments, students with stronger SRL skills are more capable of navigating digital platforms, allocating cognitive resources effectively, and engaging deeply with instructional content (Xu et al., 2023). Conversely, students with limited

SRL skills often experience difficulties in managing time, monitoring understanding, and sustaining motivation, leading to surface-level engagement and weaker learning outcomes. Prior studies emphasize that scaffolding SRL through guided reflection, metacognitive prompts, and structured learning tasks can enhance students' capacity for deep engagement and meaningful learning (Shao et al., 2023).

Within online and blended learning research, the role of self-regulated learning has increasingly been conceptualized through the Community of Inquiry (CoI) framework (Akyol & Garrison, 2008; Garrison et al., 1999). Originally comprising teaching presence, social presence, and cognitive presence, the CoI framework has been extended to incorporate learners' regulatory processes explicitly. Recent work argues that SRL constitutes a central component of learning presence, enabling learners to sustain inquiry, manage cognitive demands, and coordinate participation in collaborative learning environments (Shea et al., 2022). From this perspective, SRL is not merely an individual skill but a key mechanism that supports cognitive presence and deep learning within blended environments.

Social presence represents another critical dimension influencing learning processes in blended contexts. The concept has a long theoretical history, originating from Social Presence Theory (Short et al., 1976), which described the extent to which individuals perceive others as "real" in mediated communication. In online learning research, social presence was later incorporated into the CoI framework as a core element that supports discourse, interaction, and the development of shared understanding (Garrison et al., 1999; Akyol, 2009). Contemporary definitions emphasize learners' perceptions of peers and instructors as authentic, accessible, and emotionally engaged in online interactions (Ratan et al., 2022; Turk et al., 2022; Wut & Xu, 2021). High levels of social presence have been linked to increased motivation, satisfaction, and participation, thereby fostering opportunities for collaborative knowledge construction and deep learning (Parrish et al., 2021; Zhao & Qin, 2021).

However, recent research cautions against assuming that social presence alone guarantees meaningful learning. Shea et al. (2022) argue that social interaction must be accompanied by co-regulation and socially shared regulation of learning to support cognitive presence effectively. In complex collaborative learning environments, learners must jointly monitor progress, negotiate goals, and adapt strategies to sustain productive inquiry. Without such regulatory processes, peer interaction may remain affectively engaging but cognitively shallow. Empirical studies further suggest that poorly structured discussions, limited instructor facilitation, and unstructured peer interaction can weaken the educational value of social presence, reducing its contribution to deep learning (Demir et al., 2023; Dunmoye et al., 2024). These findings underscore the importance of designing socially rich yet pedagogically guided learning environments, where social presence aligns with cognitive and regulatory demands.

Cognitive load theory provides an additional lens for understanding learning in blended environments. Cognitive load refers to the mental effort required to process information and is commonly categorized into intrinsic load, extraneous load, and germane load (Kirschner, 2002; Sweller, 2011). In blended learning contexts, learners must often navigate multiple instructional formats, digital tools, and self-paced activities, making cognitive load management particularly critical. When extraneous load is excessive, due to unclear instructions, fragmented materials, or

poorly designed interfaces, students' capacity for deep learning is compromised (Seufert et al., 2024; Wang & Lajoie, 2023). Conversely, well-designed instructional materials that optimize intrinsic load and promote germane processing can support schema construction and deeper cognitive engagement.

Importantly, recent research suggests that cognitive load does not operate independently but interacts with learners' regulatory capacities and social learning conditions. Students with strong SRL skills are better equipped to manage cognitive demands, filter relevant information, and remain focused on learning goals (Hartelt & Martens, 2024; T. Wang et al., 2023). Likewise, socially supportive environments can help learners seek clarification, distribute cognitive effort, and maintain engagement during challenging tasks (Costley, 2019; Doo & Bonk, 2020). Within the CoI framework, these interactions underscore the interdependence of cognitive presence, social presence, and learning presence in fostering deep learning.

Despite a growing body of research examining SRL, social presence, and cognitive load, much of the existing literature has explored these constructs in isolation. There remains limited empirical evidence on how they function collectively as an integrated system influencing deep learning and learning outcomes, particularly in non-Western contexts. This gap is especially salient in teacher education, where pre-service teachers must learn to regulate their own learning while simultaneously developing competencies for designing effective learning environments for others. Accordingly, this study aims to investigate the interrelated roles of self-regulated learning, social presence, and cognitive load in shaping deep learning and learning outcomes among pre-service teachers in a blended learning environment, thereby contributing both empirically and theoretically to ongoing discussions in online and blended learning research.

Hypothesis Development

Direct Effect Hypotheses

Blended learning can be designed to integrate cognitive and social factors influencing deep learning and academic outcomes. This study examines the relationships between self-regulated learning (SRL), social presence, cognitive load, deep learning, and learning outcomes among pre-service teachers.

Cognitive load can hinder excessive deep learning but supports schema construction when well-managed. Poor instructional design increases extraneous load, reducing students' ability to engage in higher-order thinking. Thus, it is hypothesized that: **H1**: *Cognitive load negatively influences deep learning.*

Cognitive load also affects learning outcomes, as excessive cognitive demands impair knowledge retention and performance. Thus, it is hypothesized that:

H2: *Cognitive load negatively influences learning outcomes.*

Deep learning fosters critical thinking, promotes meaningful knowledge construction, and enhances long-term retention, thereby directly improving academic performance. Thus, it is hypothesized that:

H3: *Deep learning positively influences learning outcomes.*

Self-regulated learning (SRL) enables students to plan, monitor, and adjust their strategies, allowing them to manage cognitive load effectively and engage in deep learning. Thus, it is hypothesized that:

H4: *Self-regulated learning positively influences deep learning.*

Beyond deep learning, SRL improves academic performance by helping students stay motivated and optimize their cognitive efforts. Thus, it is hypothesized that:

H5: *Self-regulated learning positively influences learning outcomes.*

Social presence enhances engagement, collaboration, and knowledge-building, which fosters deeper learning in blended environments. Thus, it is hypothesized that:

H6: *Social presence positively influences deep learning.*

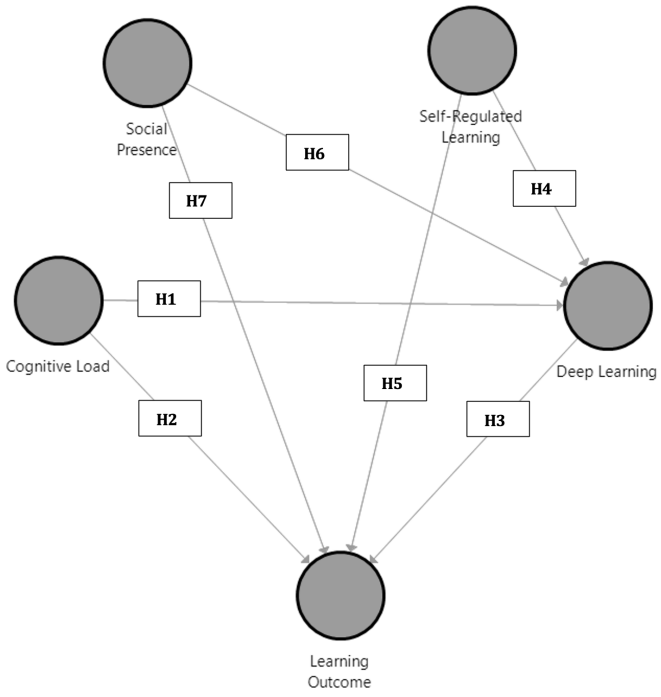
Additionally, social presence contributes directly to learning outcomes by increasing motivation and student participation. Thus, it is hypothesized that:

H7: *Social presence positively influences learning outcomes.*

These hypotheses align with the structural model (Figure 1), illustrating deep learning as a key mediating factor in blended learning environments.

Figure 1

Structural Model



Indirect Effect Hypotheses

Deep learning may mediate the effects of cognitive and behavioral factors on learning outcomes. Accordingly, the following indirect hypotheses are proposed:

Cognitive load can impair learning, but deep learning facilitates the construction of meaningful knowledge, potentially mitigating its adverse effects. Thus, it is hypothesized that:

H8: *Deep learning mediates the relationship between cognitive load and learning outcomes.*

SRL fosters deeper engagement with content, which improves academic performance through deep learning strategies. Thus, it is hypothesized that:

H9: *Deep learning mediates the relationship between self-regulated learning and learning outcomes*.

Social presence enhances interaction and engagement, but its impact on learning outcomes may depend on the type of learning involved. Thus, it is hypothesized that:

H10: *Deep learning mediates the relationship between social presence and learning outcomes.*

Method

This study investigates the interplay of self-regulated learning (SRL), social presence, and cognitive load in shaping deep learning outcomes among pre-service teachers in a blended learning environment. The blended learning environment examined in this study was intentionally designed to integrate structured face-to-face instruction with systematically organized online learning activities over a 12-week academic semester. Learning activities were distributed across synchronous (face-to-face) and asynchronous (online) modes. Face-to-face sessions were conducted weekly, focusing on interactive lectures, guided discussions, collaborative problem-solving, microteaching simulations, and project-based presentations. These sessions emphasized conceptual clarification, instructor scaffolding, dialogic interaction, and immediate formative feedback.

The asynchronous component was delivered through the university's Moodle-based learning management system (LMS), *elearning.radenintan.ac.id*, which served as the central digital learning hub. Through the LMS, students accessed weekly learning modules consisting of pre-recorded video lectures, academic readings, presentation slides, and supplementary learning resources. Each module included structured discussion forums, reflective prompts, and graded assignments designed to extend classroom learning and promote deeper cognitive engagement beyond face-to-face sessions.

Online discussion activities required students to respond to instructor-generated prompts, provide critical comments on peers' postings, and synthesize multiple perspectives. These discussions were moderated by the course instructor, who provided guiding questions, conceptual clarification, and integrative summary feedback to maintain alignment with learning objectives. Students also completed individual and group-based tasks, including lesson design assignments, short analytical essays, reflective journals, and collaborative projects, all of which were submitted via the LMS. Peer feedback and self-assessment features within Moodle were

selectively utilized to promote reflection, self-monitoring, and the regulation of learning strategies.

Interaction between students and instructors occurred through multiple channels, including in-class dialogue, LMS discussion forums, written feedback on assignments, and periodic synchronous online consultations. This blended design aimed to balance learner autonomy with instructional guidance, allowing students to regulate their learning pace while remaining cognitively and socially engaged across modalities.

A quantitative approach with a correlational research design was employed, using Structural Equation Modeling with Partial Least Squares (SEM-PLS) to analyze the relationships among SRL, social presence, cognitive load, deep learning, and learning outcomes.

Research Design

The study adopts a correlational cross-sectional survey design to examine the relationships among self-regulated learning, social presence, cognitive load, deep learning, and learning outcomes in the blended learning context described above. Data were collected at the end of the semester, after students had completed all face-to-face and online learning activities, ensuring that participants had sufficient exposure to the blended learning design. SEM-PLS was employed to analyze both direct and indirect relationships among latent variables (Hair et al., 2022). SEM-PLS was selected due to its suitability for complex models involving multiple constructs, mediation effects, and non-normal data distributions, as well as its robustness with large sample sizes and exploratory theory-building objectives.

Research Population and Participants

The research population consists of pre-service teachers enrolled in teacher education programs at Universitas Islam Negeri (UIN) Raden Intan Lampung who actively engage in blended learning courses. A stratified random sampling technique was employed to ensure proportional representation across teacher education programs. The final sample comprises 450 participants from various study programs, academic levels, and backgrounds. Participation was voluntary, without incentives or academic requirements, and all respondents signed informed consent forms in accordance with institutional ethical guidelines. The high participation rate was facilitated by coordinated communication through program coordinators and class representatives. This broad and representative sample provides a robust foundation for examining the dynamics of self-regulated learning, social presence, and cognitive load in blended learning environments for pre-service teachers. Ethical approval for this study was obtained from the university's research ethics committee, and all procedures adhered to the principles of voluntary participation, confidentiality, and informed consent. The demographic characteristics of the participants, including study programs, gender distribution, academic year, and blended learning experience, are summarized in Table 1. This diverse and representative sample provides a strong basis for examining self-regulated learning, social presence, and cognitive load in blended learning environments for pre-service teachers.

Table 1

Demographic Profile of Participants (n = 450)

Demographic Variable	Category	Frequency (N)	Percentage (%)
Teacher Education Program	Mathematics Education	50	11.11%
	Physics Education	45	10.00%
	Biology Education	55	12.22%
	Elementary Teacher Education	60	13.33%
	Early Childhood Teacher Education	40	8.89%
	English Education	50	11.11%
	Islamic Education	70	15.56%
	Arabic Education	30	6.67%
	Guidance and Counseling Education	50	11.11%
Total		450	100.00%
Gender	Male	180	40.00%
	Female	270	60.00%
Total		450	100.00%
Year of Study	First Year	120	26.67%
	Second Year	110	24.44%
	Third Year	115	25.56%
	Fourth Year	105	23.33%
Total		450	100.00%
Blended Learning Experience	Less than 1 year	150	33.33%
	1–2 years	200	44.44%
	More than 2 years	100	22.22%
Total		450	100.00%

Instrument

The instrument used in this study was designed to comprehensively measure self-regulated learning (SRL), social presence, cognitive load, deep learning, and learning outcomes in a blended learning environment, aligning with previous research. Details of the whole survey instrument, including all items and response formats, are provided in Appendix A. SRL was assessed through goal setting (SRL1), self-monitoring (SRL2), self-reflection (SRL3), effort regulation (SRL4), and metacognitive strategy use (SRL5), which are essential for independent learning in digital and face-to-face settings (Rovers et al., 2019). Social presence was measured based on peer interaction (SP1), instructor presence (SP2), emotional engagement (SP3), communication openness (SP4), and collaborative learning (SP5), as social connectedness has been shown to enhance engagement and motivation in online learning (Kreijns et al., 2022).

To examine students' cognitive load, the study utilized intrinsic load (CL1), extraneous load (CL2), germane load (CL3), perceived task difficulty (CL4), and cognitive effort (CL5), reflecting the balance between mental effort and instructional design in blended learning

(Sweller et al., 2011). Deep learning was evaluated through meaningful knowledge construction (DL1), critical thinking (DL2), application of concepts (DL3), reflective thinking (DL4), and integration of prior knowledge (DL5), as these elements are fundamental for higher-order learning (Slack et al., 2003). Lastly, learning outcomes were measured using final course grades (LO1), assignment and project scores (LO2), and assessment performance (LO3), ensuring an objective indicator of academic success.

Data Collection Procedures

Data were collected at the end of the academic semester after students had sufficient exposure to the blended learning environment. The online questionnaire was distributed through the institutional LMS, ensuring accessibility and consistency in administration. Prior to completing the survey, participants received an explanation of the study's purpose, ethical assurances, and instructions for completion. Only fully completed responses were included in the analysis.

Data Analysis and SEM-PLS Procedures

The data were analyzed using Structural Equation Modeling with Partial Least Squares (SEM-PLS), which is appropriate for examining complex relationships among latent constructs and testing both direct and indirect effects. The analysis followed a two-stage procedure: (1) measurement model evaluation, in which construct reliability and validity were assessed using indicator loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), and the Fornell–Larcker criterion; and (2) structural model evaluation, in which path coefficients, t-statistics, and p-values were examined using bootstrapping procedures. Model fit was assessed using multiple indices, including the Standardized Root Mean Square Residual (SRMR), Squared Euclidean Distance (d_ULS), Geodesic Distance (d_G), Normed Fit Index (NFI), and Root Mean Square Theta (RMS theta).

This analytical approach enabled the examination of both direct effects (e.g., SRL, cognitive load, and social presence on deep learning and learning outcomes) and indirect effects mediated by deep learning, providing a comprehensive understanding of the learning processes in the blended environment.

Validity and Reliability

Content Validity

The content validity of the questionnaire was ensured through a rigorous validation process, which confirmed that the items accurately represented the theoretical constructs of self-regulated learning, social presence, cognitive load, deep learning, and learning outcomes in the context of blended learning among pre-service teachers. The validation process involved an expert panel review of three specialists in educational psychology, instructional design, and blended learning. These experts evaluated each item based on clarity, relevance, and theoretical alignment, leading to minor refinements to enhance interpretability. A content validity index (CVI) was then calculated, where items with an item-level CVI (I-CVI) of 0.78 or higher were retained, ensuring their appropriateness. The scale-level CVI (S-CVI/Ave) of 0.90 or higher confirmed overall strong content validity.

To further validate the instrument, a pilot study was conducted with 50 pre-service

teachers, assessing the clarity and comprehensibility of the items. Participants provided qualitative feedback, leading to minor modifications to enhance readability and reduce ambiguity. The final questionnaire reflects a high level of content validity, ensuring that it effectively captures the key dimensions of blended learning experiences among pre-service teachers while aligning with established theoretical frameworks in self-regulated learning, social presence, cognitive load, and deep learning.

Reliability and Convergent Validity

The reliability and convergent validity of the measurement model were assessed using Composite Reliability (CR), Cronbach's Alpha, and Average Variance Extracted (AVE), as presented in Table 2.

Table 2

Results of Model Constructs

Construct	Loadings	Composite Reliability (CR)	Cronbach's Alpha	AVE
Cognitive Load	0.745-0.918	0.928	0.902	0.721
Deep Learning	0.915-0.956	0.970	0.962	0.868
Learning Outcome	0.978-0.989	0.988	0.982	0.965
Self-Regulated Learning	0.817-0.924	0.944	0.925	0.771
Social Presence	0.871-0.924	0.958	0.946	0.822

Note. Indicator loadings ≥ .70 indicate acceptable item reliability. Composite Reliability (CR) and Cronbach's Alpha values ≥ .70 demonstrate satisfactory internal consistency. Average Variance Extracted (AVE) values of 0.50 or higher indicate adequate convergent validity.

The results demonstrate strong internal consistency across all constructs, with CR and Cronbach's Alpha values exceeding the recommended threshold of 0.7, indicating a high level of reliability. Additionally, the AVE values for all constructs exceed 0.5, confirming adequate convergent validity, which means that each construct explains a significant portion of the variance in its respective indicators. These findings suggest that the measurement model effectively captures the intended latent variables.

Discriminant Validity

Discriminant validity was evaluated using the Fornell-Larcker criterion, as shown in Table 3.

Table 3

Discriminant Validity of Constructs

Construct	Cognitive Load	Deep Learning	Learning Outcome	Self-Regulated Learning	Social Presence
Cognitive Load	0.849				
Deep Learning	0.892	0.931			
Learning Outcome	0.691	0.791	0.983		
Self-Regulated Learning	0.913	0.882	0.658	0.878	
Social Presence	0.903	0.873	0.633	0.905	0.906

The square root of the AVE for each construct exceeds the intercorrelations with other constructs, confirming that each variable is distinct and not overly correlated with others. These results indicate that the constructs in the model measure separate theoretical concepts, ensuring their validity for structural analysis.

Model Fit Indices

The overall model fit was evaluated using multiple goodness-of-fit indicators commonly applied in Partial Least Squares Structural Equation Modeling (SEM-PLS), including the Standardized Root Mean Square Residual (SRMR), squared Euclidean distance (d_ULS), geodesic distance (d_G), Chi-square statistic, Normed Fit Index (NFI), and Root Mean Square Theta (RMS Theta), as reported in Table 4.

Table 4

Model Fit Indices

Index	Saturated Model	Estimated Model
SRMR	0.09	0.09
d_ULS	0.737	0.737
d_G	0.657	0.657
Chi-Square	1027.768	1027.768
NFI	0.052	0.052
RMS Theta	0.170	

Note. SRMR < 0.10 indicates acceptable model fit; lower values of d_ULS and d_G reflect minor discrepancies between observed and model-implied correlations; RMS Theta values below 0.20 suggest adequate outer model quality.

The SRMR, which measures the standardized difference between observed and predicted correlations, indicates an acceptable model fit when values are below 0.10. The reported SRMR value meets this criterion. The d_ULS and d_G indices assess the discrepancy between empirical and model-implied correlation matrices, with lower values indicating better fit; the obtained values suggest that the estimated model adequately represents the data structure. The Chi-square

statistic reflects overall model–data correspondence and, as expected in large-sample SEM-PLS applications, should be interpreted cautiously due to its sensitivity to sample size.

The Normed Fit Index (NFI) compares the proposed model with a null model and is often conservative in PLS-based estimation. Although the NFI value appears low, this outcome is not uncommon in complex PLS models and does not necessarily indicate poor model quality. Finally, the RMS Theta, which evaluates the degree of residual variance in the outer model, remains within acceptable limits, further supporting the adequacy of the measurement and structural models. Taken together, these indices indicate that the proposed model demonstrates an acceptable overall fit and is suitable for hypothesis testing and further structural analysis.

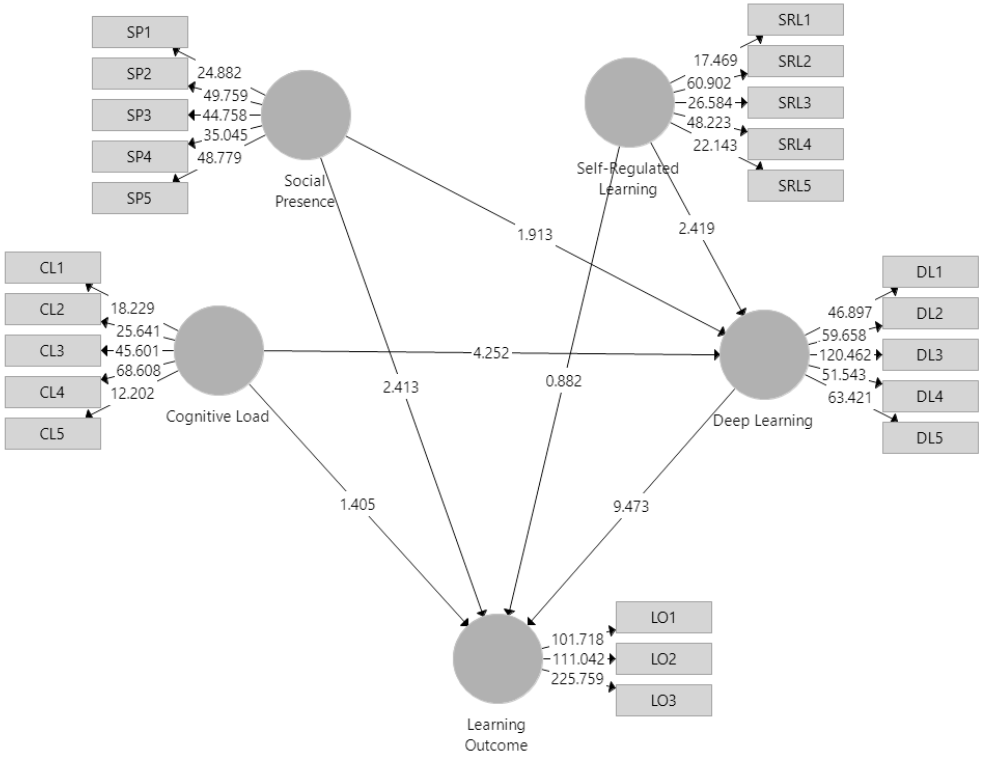
Results

Path Coefficients Analysis

The structural model was evaluated using path coefficient analysis, as presented in Figure 2 and Table 6. The results provide empirical insights into the relationships between cognitive load, self-regulated learning, social presence, deep learning, and learning outcomes within a blended learning environment.

Figure 2

Path Coefficient



The findings indicate that cognitive load has a significant influence on deep learning (β = 0.409, t = 4.252, p < 0.001), contradicting H1, which hypothesized an adverse effect. This suggests that cognitive load, when well-managed, can facilitate deep learning rather than hinder it. However, the direct effect of cognitive load on learning outcomes was not statistically significant (β = 0.153, t = 1.405, p = 0.161), failing to support H2, which implies that cognitive load alone does not directly determine academic success but rather operates through deep learning.

Deep learning emerged as a strong predictor of learning outcomes (β = 0.974, t = 9.473, p < 0.001), providing strong support for H3, which proposed that deep learning directly enhances academic performance. While the analysis confirms the directional influence of deep learning on outcomes, it is also plausible, based on reciprocal learning theories, that positive academic outcomes may, in turn, reinforce students' engagement in deeper learning strategies. However, this reciprocal effect was not examined in the present model and warrants further investigation.

Table 5

Path Coefficient

Hypotheses	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Cognitive Load -> Deep Learning	0.409	0.406	0.096	4.252	< 0.001*
Cognitive Load -> Learning Outcome	0.153	0.141	0.109	1.405	0.161
Deep Learning -> Learning Outcome	0.974	0.979	0.103	9.473	< 0.001*
Self-Regulated Learning -> Deep Learning	0.29	0.284	0.12	2.419	0.016*
Self-Regulated Learning -> Learning Outcome	-0.104	-0.09	0.118	0.882	0.378
Social Presence -> Deep Learning	0.241	0.248	0.126	1.913	0.056
Social Presence -> Learning Outcome	-0.262	-0.265	0.108	2.413	0.016*

Note. Standardized path coefficients are shown. Paths marked with an asterisk () are statistically significant (p < .05); T statistics greater than 1.96 indicate significant effects based on bootstrapping.*

Self-regulated learning was found to significantly predict deep learning (β = 0.290, t = 2.419, p = 0.016), supporting H4, which posited that students with strong SRL skills are more likely to engage in deep learning. As indicated in Table 5, however, self-regulated learning did not have a direct impact on learning outcomes (β = -0.104, t = 0.882, p = 0.378), failing to support H5. This suggests that while SRL enhances learning engagement, its effects on academic performance are primarily indirect, operating through the process of deep learning.

Social presence exhibited a moderate but statistically insignificant effect on deep learning (β = 0.241, t = 1.913, p = 0.056), failing to support H6, which hypothesized a positive relationship. This indicates that while interaction and perceived connectedness may contribute to engagement, their direct influence on deep learning is not substantial. Interestingly, social presence had a negative influence on learning outcomes (β = -0.262, t = 2.413, p = 0.016), contradicting H7, which predicted a positive effect. This unexpected finding suggests that while social presence can foster engagement, excessive reliance on social interactions without structured learning strategies may detract from academic performance.

Indirect Effects Analysis

The indirect effects analysis examined whether deep learning mediates the relationships between cognitive load, self-regulated learning, social presence, and learning outcomes. The results in Table 6 provide empirical evidence supporting some of the proposed mediation effects.

Table 6

Path Coefficient for Indirect Effects.

Hypotheses	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Cognitive Load -> Deep Learning -> Learning Outcome	0.399	0.397	0.101	3.948	< 0.001*
Self-Regulated Learning -> Deep Learning -> Learning Outcome	0.282	0.276	0.118	2.385	0.017*
Social Presence -> Deep Learning -> Learning Outcome	0.235	0.246	0.135	1.743	0.082

Note. Indirect effects were tested using bootstrapping. Asterisks () indicate statistically significant mediation effects (p < .05). Indirect paths with T statistics > 1.96 are considered significant.*

The mediation analysis indicates that cognitive load indirectly influences learning outcomes through deep learning (β = 0.399, t = 3.948, p < 0.001), confirming H8. This finding suggests that while cognitive load does not directly affect learning outcomes, it influences students' engagement in deep learning, thereby enhancing their academic performance. This emphasizes the importance of managing cognitive load effectively in blended learning environments to foster more profound learning experiences.

Similarly, self-regulated learning has a significant influence on learning outcomes through deep learning (β = 0.282, t = 2.385, p = 0.017), supporting H9. This suggests that students with strong self-regulation skills are more likely to engage in deep learning strategies, resulting in improved academic performance. The result reinforces the critical role of self-regulation as an enabler of deep learning, rather than a direct predictor of academic success.

However, the indirect effect of social presence on learning outcomes through deep learning was not statistically significant (β = 0.235, t = 1.743, p = 0.082), failing to support H10. This suggests that while social presence may enhance student engagement, it does not

necessarily lead to improved academic performance unless accompanied by other effective learning strategies. This finding suggests that social presence alone is insufficient for improving learning outcomes and must be supplemented by instructional designs that foster meaningful cognitive engagement.

Discussion

The findings of this study provide significant insights into how cognitive load, self-regulated learning, and social presence influence deep learning and learning outcomes within a blended learning environment intentionally designed to promote student-centered learning. In this context, the blended approach combined asynchronous online modules (delivered via Moodle at elearning.radenintan.ac.id) with in-person class sessions, incorporating reflective activities, group discussions, and problem-based assignments to encourage cognitive engagement, metacognition, and collaborative interaction. These findings are particularly relevant for Indonesia's higher education system, where blended learning has been increasingly adopted, but challenges persist in fostering deep engagement and self-regulated learning among students (Supriyadi et al., 2023; Widjaja & Aslan, 2022). Since many Indonesian students come from educational backgrounds emphasizing rote memorization and teacher-centered instruction (Haryanto, 2024), transitioning to student-centered blended learning requires instructional strategies that effectively support cognitive engagement, metacognition, and meaningful interaction.

A notable finding of this study is that cognitive load has a positive influence on deep learning. This challenges the conventional assumption that cognitive load primarily hampers learning (Brockbank & Feldon, 2024). Instead, the results suggest that when cognitive load is well-managed, it can facilitate schema construction and deeper cognitive processing (Clark, 2024; Frey et al., 2022). While this reflects a cognitive perspective, the study adopts a socio-cognitive theoretical framework, which integrates both individual information processing and social interaction in learning. Within this framework, cognitive development occurs not only through individual internalization but also through collaborative meaning-making and co-regulated learning. The use of structured collaboration in the blended environment aligns with this view, as collaborative tasks were designed to activate germane cognitive load while enabling shared regulation and social negotiation of understanding. This is consistent with Cognitive Load Theory, which distinguishes between extraneous, intrinsic, and germane cognitive load. While excessive extraneous load may hinder learning, an optimal level of intrinsic and germane load—especially within collaborative settings—can enhance comprehension and problem-solving abilities (Leppink et al., 2013). However, cognitive load was not found to directly influence learning outcomes, indicating that its impact on academic performance is realized primarily through deep learning. This finding has significant implications for instructional design in Indonesia, where students often struggle with self-directed learning due to their reliance on structured, instructor-led teaching (Asyhari & Islamia, 2023). The challenge for educators is to design learning experiences that promote meaningful engagement and peer collaboration while carefully managing cognitive demands.

The results also confirm that self-regulated learning plays a crucial role in deep learning, supporting previous research that emphasizes the importance of metacognitive strategies in

student learning (Panadero et al., 2021). Self-regulated learners tend to engage more deeply with course content, effectively managing their time and cognitive resources to enhance understanding. However, this study found no significant direct effect of self-regulated learning on learning outcomes, indicating that self-regulation alone does not guarantee academic success unless it is channeled into deep learning processes. This aligns with research suggesting that self-regulated learning must be combined with structured scaffolding and instructional supports to be fully effective (Munshi et al., 2023). In the Indonesian education system, where students often rely on external motivation rather than intrinsic learning strategies (Asyhari & Islamia, 2023; Misbah et al., 2022), providing explicit guidance on self-regulated learning techniques, such as self-monitoring, goal setting, and reflective practices, can help students develop autonomy in their learning.

One of the more unexpected findings is that social presence did not significantly influence deep learning and had a negative impact on learning outcomes. Prior research has highlighted the role of social presence in fostering engagement and motivation in online and blended learning environments (Shi et al., 2021; Zhong et al., 2022), yet the results of this study suggest that social presence alone is insufficient for promoting deeper cognitive engagement. This finding aligns with studies indicating that while social presence enhances student satisfaction, it does not necessarily contribute to conceptual understanding unless interaction is structured to facilitate higher-order thinking (Lee, 2014). In Indonesia, where students often participate in online discussions passively or superficially, more structured collaborative learning activities, such as inquiry-based discussions, debate tasks, and problem-solving exercises, may be needed to ensure that social presence translates into meaningful academic engagement. Furthermore, the adverse effect of social presence on learning outcomes in this study likely stems from the design of the learning environment, in which asynchronous peer interactions were not always clearly aligned with instructional goals. As a result, some students may have engaged in off-task or non-substantive discussions, reducing the overall effectiveness of their learning experience. This suggests that excessive reliance on peer interaction without clear instructional goals, as observed in several discussion forums during the course, may serve as a distraction rather than a facilitator of learning (Wang et al., 2023). This highlights the importance of designing social interactions directly tied to learning objectives, ensuring they enhance rather than hinder student comprehension.

The mediation analysis further underscores the importance of deep learning as a mechanism linking cognitive, self-regulatory, and social factors to academic success. The significant mediation effect of deep learning in the relationship between cognitive load and learning outcomes supports the view that optimal cognitive challenges can enhance academic performance when they lead to deeper engagement (Jeong et al., 2024; Martin, 2018; Skulmowski & Xu, 2022). Similarly, the mediation effect of deep learning in the relationship between self-regulated learning and learning outcomes confirms that self-regulation alone is not a direct predictor of academic achievement but plays a crucial role in fostering deep learning behaviors (Panadero et al., 2021). However, the non-significant mediation effect of deep learning in the relationship between social presence and learning outcomes suggests that social presence does not inherently improve academic success unless coupled with structured, cognitively engaging learning activities.

Despite the methodological rigor of this study, several potential threats to validity merit consideration. First, the reliance on self-reported data introduces the possibility of self-report bias, particularly for constructs such as self-regulated learning and social presence that are closely tied to learners' self-perceptions. In the Indonesian higher education context, where students may be inclined toward compliance-oriented responses, social desirability effects cannot be entirely excluded. To mitigate this risk, participation was voluntary and anonymous, with no academic incentives or consequences, thereby reducing evaluation apprehension and encouraging candid responses. Second, common method bias may arise because most constructs were measured using a single survey administered at one time point. To address this concern, the study employed procedural remedies, including careful item wording and separation of construct indicators across the questionnaire, as well as statistical checks. Evidence of discriminant validity using the Fornell–Larcker criterion indicates that the constructs were empirically distinct, reducing the likelihood that observed relationships were driven primarily by shared measurement artifacts rather than substantive theoretical links. Third, the correlational SEM-PLS design limits causal inference. Although the structural model specifies theoretically grounded directional paths, the findings should be interpreted as associative rather than causal. This limitation is particularly relevant given the potentially reciprocal relationships between deep learning and learning outcomes. Path directions were therefore justified through established theoretical frameworks, including Cognitive Load Theory and socio-cognitive perspectives on learning, while recognizing that longitudinal or experimental designs are needed to establish causal mechanisms more conclusively. Finally, contextual and cultural specificity represents both a strength and a limitation. Conducted within a single Indonesian public university, the study reflects pedagogical traditions shaped by teacher-centered instruction and varying levels of learner autonomy and digital readiness. While this enhances ecological validity and contextual relevance, it constrains generalizability beyond similar settings. To support transferability, the blended learning design, instructional practices, and LMS-mediated activities were described in detail.

Limitation

This study has several limitations that should be taken into account when interpreting the findings. First, the sample was drawn from a single public university in Indonesia, which may limit the generalizability of the results to other institutional, cultural, or disciplinary contexts. Second, although the sample size was relatively large, participation was voluntary, raising the possibility of self-selection bias. Third, the reliance on self-reported data may not fully capture students' actual learning behaviors or cognitive engagement. Finally, the non-experimental and cross-sectional design prevents conclusions about causal mechanisms or developmental changes over time.

Conclusion

This study highlights the critical role of deep learning in mediating the effects of cognitive load, self-regulated learning, and social presence on learning outcomes in a blended learning environment, with implications for Indonesia's higher education system. The findings reveal that cognitive load, when well-managed, fosters deep learning, emphasizing the need for instructional designs that optimize rather than minimize cognitive demands. Self-regulated learning significantly enhances deep learning but does not directly influence learning outcomes,

reinforcing the importance of structured interventions to develop students' metacognitive skills. Social presence, while often associated with engagement, was found to have no significant effect on deep learning and negatively impacted learning outcomes, suggesting that unstructured peer interactions may serve as distractions rather than facilitators of academic success. These results underscore the necessity of carefully designing blended learning environments that promote meaningful cognitive engagement, provide explicit support for self-regulation, and structure social interactions to enhance rather than hinder learning. Given the growing adoption of blended learning in Indonesia, future research should further explore the role of instructional strategies and technological innovations in strengthening deep learning processes to optimize student success in digital and hybrid classrooms.

Implications for Instructional Design, Policy, and Educational Technology

The findings carry important implications for instructional design and higher education policy. At the pedagogical level, the results suggest that blended learning should not merely reduce cognitive demands but instead optimize cognitive challenge through carefully structured tasks that promote deep learning. Explicit scaffolding for self-regulated learning, such as guided reflection, goal-setting activities, and formative feedback, should be embedded within both online and face-to-face components. From a policy perspective, institutions should move beyond modality-based adoption of blended learning and invest in faculty development focused on learner-centered design, co-regulated collaboration, and assessment for deep learning. At the technological level, adaptive learning systems and learning analytics tools could be leveraged to monitor students' cognitive load and self-regulatory behaviors, enabling timely instructional interventions.

Future Research Directions

Future studies should extend this work by employing multi-institutional samples to enhance external validity and cross-cultural comparison. Longitudinal designs would enable researchers to investigate how self-regulation, cognitive load, and deep learning develop over time. Experimental or quasi-experimental studies could further clarify causal pathways by manipulating instructional design features, levels of cognitive challenge, or forms of structured collaboration within blended environments.

Declarations

Ethics Statement

This study was reviewed and approved by the Research Ethics Committee of Universitas Islam Negeri Raden Intan Lampung. All participants provided informed consent prior to data collection. Participation was voluntary, and respondents were assured of anonymity and confidentiality throughout the research process.

Conflict of Interest Statement

The authors declare that they have no conflicts of interest associated with this study.

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AI Use Statement

No generative artificial intelligence tools were used in data collection, analysis, or interpretation.

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Appendix A. Survey Instrument

All constructs in this study were measured using a structured questionnaire with multiple items per construct. Items were developed based on a review of relevant literature and adapted to the blended learning context for pre-service teachers. Each item used a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

1. Self-Regulated Learning (SRL)

No	Item Statement
1.1	I set specific learning goals before starting my online or offline study.
1.2	I monitor my learning progress regularly during blended courses.
1.3	I reflect on my performance and try to improve my learning strategies.
1.4	I continue studying even when the content is difficult or uninteresting.
1.5	I use techniques such as summarizing and creating concept maps to better understand the material.

2. Social Presence

No	Item Statement
2.1	I feel comfortable communicating with my classmates online.
2.2	I perceive my instructor as present and responsive in the learning process.
2.3	I feel emotionally connected with peers during collaborative activities.
2.4	I can openly share ideas and opinions in online or in-person discussions.
2.5	Working in teams helps me better understand the course material.

3. Cognitive Load

No	Item Statement
3.1	The content of this course is inherently complex.
3.2	I find it challenging to follow the instructions and navigate the LMS.
3.3	I make extra effort to organize information for better understanding.
3.4	I feel overwhelmed by the number of tasks required in this course.
3.5	I concentrate hard to make sense of the learning materials.

4. Deep Learning

No	Item Statement
4.1	I try to relate new concepts to what I already know.
4.2	I critically evaluate information before accepting it as accurate.
4.3	I apply what I have learned to solve real-world problems.
4.4	I often think about how I can improve my understanding of the material.
4.5	I integrate knowledge from different topics or courses.

5. Learning Outcomes

No	Item Statement
5.1	I have achieved high grades in this course.
5.2	I perform well in assignments and collaborative projects.
5.3	I can demonstrate my understanding through assessments and exams.

This survey instrument was pilot-tested for content validity and reliability with a sample of 50 students before full deployment. The Cronbach's alpha for each construct exceeded 0.80, confirming internal consistency. Future studies are encouraged to validate this instrument across

diverse educational contexts.

Disconnected in the Digital Age: Barriers to Flow in Online Learning

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Abstract
Disengagement among students learning online in higher education is an enduring challenge that can undermine learning outcomes, retention, and overall satisfaction. While engagement is widely recognized as essential to academic success, the unique conditions of online learning, such as reduced interpersonal interaction, feelings of isolation, and competing external demands, often hinder meaningful participation and enjoyable experiences. Using a hermeneutic phenomenological approach, this study applied flow theory (Csikszentmihalyi, 2008) to better understand the experiences of online students and the barriers to achieving an optimal state of learning. Data were collected through written reflections, interviews, and journaling with Interpretive Phenomenological Analysis (Smith et al., 2022) used to interpret findings of non-flow. The research highlighted how lack of interest, time, resistance to distractions, and prior experience in education prevents students from experiencing flow. This unique, reflective, and human-sensitive methodology encouraged a richer understanding of non-flow and offered insights into the stimuli and inhibitors to flow. The implications for students and higher education providers are encouraging better awareness of distractions and how to focus attention, as well as the potential for gaining experience in industry to nurture interest and personal connection to learning.

Keywords: Engagement, flow, online education, higher education, teacher education

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Student engagement is a cornerstone of effective higher education practice, yet disengagement remains a pervasive challenge, particularly in the online learning environment. Engagement is a multidimensional construct encompassing behavioral, emotional, and cognitive domains which, collectively, can influence students' academic success and personal development (Fredricks et al., 2004). Within this construct, engagement can also be understood through the lens of flow theory, which describes a state of deep focus and immersion that occurs when an individual's skills are appropriately matched to the challenges of the activity (Csikszentmihalyi, 2008). However, achieving this optimal state of engagement in virtual settings may be particularly challenging due to structural, technological, and psychosocial barriers (Redmond et al., 2018).

Flow theory emphasises the importance of clear and focused attention on a task, and a balance between challenge and skill to reach optimal enjoyment, or flow (Nakamura & Csikszentmihalyi, 2002). Through the application of flow theory, a multifaceted approach to studying online engagement could be applied. Each dimension of engagement can be studied simultaneously through flow and how they dynamically interrelate with a students' unique online environment. Csikszentmihalyi (2014) found that when learning is intentional and intrinsically motivated, students experience personal growth from improving the complexity of their skills. However, online higher education students often lack the necessary study conditions, resulting in boredom and frustration, conditions which are unconducive for flow. Research has shown that poorly designed online courses, limited interaction with instructors and peers, and feelings of isolation frequently undermine students' ability to experience engagement, leading to reduced motivation and persistence (Martin & Bolliger, 2018; Rovai, 2002). Additionally, external factors, such as competing work or family responsibilities and unequal access to technology, exacerbate these challenges, further widening disparities in academic outcomes for online students (Stone & O'Shea, 2019a).

Given the increasing prevalence of online education, understanding the factors that inhibit or promote flow is essential. Rather than allowing students to study in boredom, frustration, and apathy, the challenge lies in exploring and understanding how the experience of studying online can be more worthwhile, more enjoyable, and even fun. Research confirms that flow results in not only intrinsically motivated experiences and personal growth but can also improve an individual's wellbeing and mental health (Carpentier et al., 2012; Tse et al., 2021), further highlighting the need for research in this area. The overarching question that drove this study was, what are higher education student experiences with flow in online learning environments? While some participants in this study did experience flow, this article focuses on the inhibitors to students' flow experiences, which are seldom researched through a phenomenological lens. The hermeneutic phenomenological study of flow was a reminder that research which is human centred, respects the voices and experiences of higher education students learning online, and encourages multiple ways of viewing online student engagement (Kumasaka, 2024). By understanding these non-flow experiences, the study aimed to contribute to the growing body of literature that informs strategies to foster meaningful and deep engagement, or flow, in online learning environments.

Background

While higher education is a choice for many adults, it is often thought of as a means to future financial security via meaningful, well-paid employment (Laming et al., 2016). It is unfortunate that many students consider study to be boring and exhausting and are only motivated by the external rewards, as this has been reported to inhibit learning rather than promote it (Bryson & Hand, 2007; Csikszentmihalyi, 1982). As such, students' enjoyment

and motivation related to learning become key considerations for higher education. When students experience flow, they are intrinsically motivated (Engeser & Rheinberg, 2008; Meyer et al., 2016) and thus, the goal is to find activities that are rewarding themselves (autotelic) and not reliant on external incentives. There is limited understanding about how this occurs and the barriers that may limit these experiences for students in the online learning environment in higher education.

Online learning in higher education cultivates a ubiquitous learning environment, making it more challenging for educators to manipulate the social context and other factors that create a physical learning environment which are conducive to flow. The pre-conditions of flow must be fulfilled, and time and resistance to distractions are the most common impediments (Csikszentmihalyi & Csikszentmihalyi, 1988). Students often struggle to dedicate enough time to their studies due to the pressures of everyday living and endless digital distractions which often compromise commitment (Xavier & Meneses, 2022). Csikszentmihalyi and Csikszentmihalyi (1988) believed that partial commitment and energy spent on an activity leads to partial fulfilment and potentially inhibits the flow experience. Although some people may be satisfied with shallow engagement and deriving little satisfaction from their studies, this is not an optimal pursuit of education.

Online Student Engagement

Engagement is a multifaceted and complex term because often its three dimensions - behavioral, emotional, and cognitive - overlap. Dimensions of engagement are not isolated, but dynamically interrelated (Fredricks et al., 2004). Guthrie and Wigfield (2000) and Guthrie and Anderson (1999) reasoned that research on engagement should consider all three dimensions of engagement to allow for a more holistic characterisation of the individual. Further, Muir et al. (2019) advocated for longitudinal studies to capture engagement fluctuations over time. Online student engagement in higher education is not a new field of research; however, most studies have focused on a single dimension of engagement.

Previous research in online engagement in higher education has shown that active student participation, instructor engagement, and effectively designed learning environments contribute to better student engagement and self-efficacy (Allen & Seaman, 2014; Bedi, 2023; Bourelle et al., 2016; Getenet & Tualaulelei, 2023; Moore & Greenland, 2017; Pittaway & Moss, 2014; Stone et al., 2016; Turk et al., 2024). Some studies have argued that observable behaviors (asking questions, frequency of viewing and accessing content, and posting responses on the learning management system (LMS)) are often mistaken for engagement but are not necessarily signs of quality engagement (Dixon, 2015; Hranstinski, 2009). Hranstinski (2009) and Martin and Bolliger (2018) found that quality engagement is a complex process of forming relationships and interactions between the instructor and students and is supported by realistic learning opportunities. Research has identified the importance of understanding student engagement in the online learning environment to assist with issues of isolation and retention (Gray & DiLoreto, 2016; Pinchbeck & Heaney, 2022; Stone et al., 2016; Waugh & Su-Searle, 2014). With rapid changes to digital technologies, such as AI, it is even more important to understand how students engage in the online learning environment.

Flow Theory

The identification of different types of engagement and their significance to online learning warranted further investigation via a research approach that captured and differentiated among three dimensions: cognitive, behavioral and emotional engagement. An extensive range of high level cognitive, behavioral, and emotional engagement indicators (high effort, concentration, happy feeling, interest, and intrinsic motivation) are identified in

flow theory, making flow's application to studies of engagement, where all three dimensions can be studied simultaneously, an appropriate extension of engagement research. Landhausser and Keller (2012) reported that flow theory positively influenced cognitive, behavioral, and emotional characteristics of an individual, which provided potential for the application of flow theory to studies of multidimensional engagement. Through the application of flow theory to engagement research, all three types of engagement in the current study could be explored simultaneously; this provides a new lens to view online student engagement, which few studies have applied to research in this context.

Flow theory explains that when people experience optimal enjoyment from a task, they experience a state of consciousness characterised by deep concentration and absorption with the task, when the task is appropriately challenging for a person's skill level. This is known as "flow" (Csikszentmihalyi, 1975, 2008). A consequence of flow is that the completed activity becomes intrinsically autotelic (that is, rewarding in itself) and the person wants to repeat the activity (Csikszentmihalyi, 1975). Studies using flow have reported that people with autotelic personalities are more likely to experience flow and report high levels of improved wellbeing (Carpentier et al., 2012; Heutte et al., 2021; Tse et al., 2021). Furthermore, Landhausser and Keller (2012) found that cognitive, behavioral, and emotional factors were improved as a consequence of flow experiences, thus making studies of flow highly relevant to engagement research and particularly interesting for understanding how this occurs in the online learning environment.

A variety of interrelated concepts have been studied in combination with flow in the online learning environment, such as the role of flow on learner motivation and behavior in distance education (Liao, 2006), and to predict online students' satisfaction and intention to continue studying (Shin, 2006). Guo et al. (2016) found that telepresence (the feeling of being physically present) was the most important factor influencing flow in online learners in higher education, and Chaker et al. (2022) found that flow experiences resulted in higher achievements and retention of online students in a Massive Open Online Course (MOOC). Most studies on flow in online learning involve quantitative data and lack a holistic understanding of the relationship interplay between the learner and the context.

The Current Study

This study emerged from a desire to move away from the current flow research, which focuses heavily on measuring flow in a variety of diverse contexts through quantitative data (Bakker, 2008; Heutte et al., 2021; Liu et al., 2022; Moneta, 2021; Norsworthy et al., 2021). As flow theory hails from positive psychology, where the research subject is what goes right in life (Seligman, 2002), the primary aim of this study was to explore positive student experiences to better understand what fosters meaningful engagement or flow experiences. Through exploration of flow experiences which have already been reported (see Kumasaka, 2025a), the research also revealed gaps and barriers that hinder flow, making it clear how flow and non-flow experiences are interconnected. Thus, the current paper focuses on understanding these experiences of non-flow and explores the inhibitors to the flow experience. The concept of non-flow in this study is not synonymous with disengagement but rather identifies an experience that may still reflect disengagement or engagement, either behavioral, emotional, and/or cognitive, but for various reasons, does not reflect the unique flow experience, where all three engagement types are experienced simultaneously. In this way, this paper uniquely explores how non-flow manifests in online higher education students and explores the relationship between context and the learner's cognitive, behavioral, and emotional engagement, a key gap in online learning research.

This study assists online education providers by providing practical understanding and recommendations about improving student engagement but also contributes conceptually to flow research. Through application of a humanistic approach - hermeneutic phenomenology - the study offered the possibility of understanding the non-flow experiences in the context of the higher education online learning environments that are not yet well understood and are underexplored in flow research. The uniqueness of the methodologies chosen provided holistic insights into the internal and external barriers to flow which may be overlooked with other methodologies. This unique way of looking at flow and non-flow experiences provides a broader view of student experiences when learning online and does not categorize the experience as either engagement or disengagement, but views students as complex and multi-layered individuals. Rather than viewing the issue as a problem to solve, this approach allowed student experiences to be explored in a unique way and to encourage a more thoughtful and tactful action to be embraced. It allowed a sympathetic exploration of the student experience and an opportunity to discover the extraordinary in the ordinary experiences of studying online.

Methodology

This study used a hermeneutic phenomenological approach, ensuring participants' voices and lived experiences were honoured (Kumasaka, 2024). The study was approved by Curtin University (Human Ethics Approval # HRE2019-0155) and all participants provided informed consent before involvement in the study.

Theoretical Lens

Hermeneutic phenomenology was the most appropriate methodology for this study as it offered a unique perspective about the lived experience of flow or non-flow. It encouraged discovery of moods, emotions, feelings, and sensations involved with participants' experiences and enabled enquiry about how the experience unfolded and what it all meant to the individuals and their lives (van Manen, 1990; Wilson, 2015). The distinction between hermeneutic phenomenology and other phenomenologies is the belief that the individual and their world are inseparable (Heidegger, 1978) and using this hermeneutic approach ensured that the distinctive environment and context of each participant was considered in the study.

Researcher Positionality

In hermeneutic phenomenology, the researcher is not a distant observer but an active participant in the interpretive process. Acknowledging this, we recognise that our own experiences, understandings, and preconceptions are inseparable from the study. Heidegger's (1978) notion of situatedness remind us that interpretation always begins with the researcher's prior knowledge and experiences from living in the world. Thus, rather than striving for objectivity or detachment, we approached this study with an openness to questioning our own assumptions and engaging reflectively with the phenomenon. A process of explicitly identifying our presumptions, based on personal experiences and our own everyday understandings through a reflective journal and memoing were employed.

Our professional backgrounds and pedagogical commitments shaped the lens through which we encountered the participants' experiences. These insights were not treated as biases to be eliminated but as necessary starting points which informed interpretive understanding. Consistent with the hermeneutic circle, a key philosophical concept where interpretation between specific parts inform the whole context and vice versa (Heidegger, 1978), we moved iteratively among our preunderstandings, participants' accounts, and emerging interpretations, allowing each to inform and reshape the other throughout the study (see Kumasaka, 2025b).

This process of interpretation was documented through researcher memos and reflective journalling, which began prior to data collection, continued during data collection, and extended into the analysis and writing stages, enabling development and documentation of interpretations efficiently over the course of the study (Patterson & Williams, 2002).

The research process was transformative, prompting us to reconsider our pedagogical practice and deepening our awareness of how our lifeworld intersects with the phenomena we seek to understand. The hermeneutic tradition also included a final reflection, and it was insightful and transformational to see our initial presumptions about how students engage with online learning had been overturned. As such, the knowledge produced is not static or detached but is a living, dynamic reflection of the interplay between researcher, participants, and the world we share.

Context and Participants

Participants in the study (N = 596) were enrolled in an Australian public university in a fully online teacher education program. Participants were from undergraduate and postgraduate programs, both male and female, with ages ranging between 18-50+ years and residing in locations across Australia. Two undergraduate units and two postgraduate units were identified and deemed appropriate, which included students who had already completed their first year at university, to ensure participants had adequate time to experience fully online study. Most participants were first-time online students, and many were also first-time students to higher education. All 596 students across four units were offered the opportunity to participate in any of the four reflective writing opportunities and invited to an interview. A large sample size was originally pursued to accommodate participant attrition and fatigue over the course of the study. The researchers were not involved in the units selected and did not instruct nor provide grades to the students in the study.

Data Collection

Hermeneutic phenomenology requires reflection and description of the experience; therefore, complementary techniques were used to collect first-person accounts of participants' lived experiences with flow or non-flow in the online learning environment. Stage 1 consisted of collecting written reflections at four different intervals across the twelve-week teaching period. The "Flow Question" (Csikszentmihalyi & Csikszentmihalyi, 1988), which describes a flow experience, was used as a prompt for participants to write reflectively about their experiences. Students in the four identified units were sent an email inviting them to participate in the study with a link to the reflective writing activity which could be completed online. A total of 81 participants responded to the Flow Question (n = 81): "Consider the three situations below and have you have felt this way over the past 3 weeks when learning online"?

- My mind isn't wandering. I am not thinking of something else. I am totally involved in what I am doing. My body feels good. I don't seem to hear anything. The world seems to be cut off from me. I am less aware of myself and my problems.
- My concentration is like breathing. I never think of it. I am really quite oblivious to my surrounding after I really get going. I think that the phone could ring, and the doorbell could ring, or the house burn down or something like that. When I start, I really do shut out the whole world. Once I stop, I can let it back in again.
- I am so involved in what I am doing. I don't see myself as separate from what I am doing.

(Csikszentmihalyi & Csikszentmihalyi, 1988)

If participants answered "yes" to the question, it was identified as a flow experience and they were asked to write reflectively describing that experience. If they answered "no" they were still asked to write reflectively about their online learning experience during the previous 3 weeks. By the end of the teaching period 129 written reflections were captured. Stage 2 of data collection consisted of semi-structured interviews (male, n = 3, female, n = 5) conducted fully online using WebX. These interviews ranged from 35 minutes to 1 hour and 20 minutes in duration and were recorded. Interviews could only be conducted with participants who provided consent, and eight participants were interviewed. As the interviews were focused on the idiographic experience (the individual) with the phenomenon, interview questions differed among individuals and questions were often leading, based on the participants' written reflections, which made each interview unique. In hermeneutic phenomenology, this is completely expected with interviews and acceptable practice (Patterson & Williams, 2002). Researcher memoing, journalling, and field notes were also used during the phenomenological process of collecting and interpreting the data.

Data Analysis

Data were analysed by adapting Smith et al.'s (2022) interpretive phenomenological analysis (IPA) approach. Analysis and interpretation were not isolated processes completed after data collection as in traditional research, but were, rather, iterative processes conducted throughout the entire study. Through the researcher's reflective journal and notes, ideas and interpretations were tracked as they occurred. The frequent moving back and forth between understanding specific parts of the data and the whole, applying the hermeneutic circle tradition (Heidegger, 1978) ensured that the interpretation contributed to the development and understanding of the phenomenon in the study (Kumasaka, 2025b).

To analyse the data through the IPA process, initial interpretations and exploratory notes were identified from the written reflections, and the interview data and written reflections for each of the eight interviewees were combined. Personal experiential statements were clustered and themes were developed. After individual analysis, cross-case analysis and group experiential themes were developed. Finally, a variety of interpretive and descriptive texts were created to communicate the findings for the phenomenon of flow in a narrative style. However, if flow was not experienced, no narrative was created. For the purposes of this paper, group themes which were identified and interpreted as non-flow or inhibitors to flow are reported and discussed here.

Results

The study revealed that flow is an elusive experience for students studying online with approximately three-quarters of participants unable to experience it. This does not mean that these participants were necessarily disengaged but that their engagement experiences were varied and complex. Some participants displayed high levels of behavioral, emotional, and/or cognitive engagement, but still did not experience flow. The findings revealed several key group themes which were barriers to flow experiences in this study, such as lack of time, resistance to distractions, personal characteristics, lack of supportive relationships, and lack of interest and prior experience in education. The findings revealed new insights, such as the importance of prior experience in the relevant industry and supportive relationships in fostering flow, highlighting the importance of the social and emotional dimensions to learning online.

Lack of Time

Just over half of the participants found that time was an inhibitor to their experience studying online and time was the leading barrier to flow in this study. Participants reported "my work and family commitments mean that I don't have the time available". Having time to study was an important recognition for many participants in this study who either consciously made time in their busy schedules to focus on study or relayed simply not having enough time to study. It was clear that participants who experienced flow deliberately dedicated enough time to study, reporting "once a week I have a dedicated day", and those who did not prioritise enough time were not able to experience flow, a finding which confirms the precondition of time for flow. Although this does not mean that all students who prioritised time experienced flow, but that when appropriate time was allocated to study, it appeared to improve student enjoyment, satisfaction with learning, and quality of work produced.

Resistance to Distractions

The second most reported barrier to flow in this study was the inability to resist distractions and participants reported "when you're studying at home you have to coexist with all the things that are in your life, that could be the laundry you're staring at, or the cat meowing. You can't separate yourself from your environment". Approximately one quarter of the participants in this study reported being distracted as a major impediment to their quality time spent studying, stating "checking a recipe, checking Instagram, start chatting to someone", and "other requirements of my daily life consume me", which could have inhibited their ability for flow experiences. Findings identified that family and technology were the biggest distractions and posed challenges to quality time for study and flow experiences, which left participants feeling helpless or out of control. While some participants' procrastination can be interpreted as lack of interest in their learning, it also reflects their lack of intrinsic motivation, an attribute commonly associated with flow.

Personal Characteristics

Not all personality traits are conducive to flow experiences, and this was reflected in the participants in this study. Through observations and interpretations of the data, some participants displayed characteristics of over-thinkers and showed lack of confidence in themselves with one participant stating, *"*I question everything*"* and another participant reported, "I find myself waking up at night thinking about the unit tasks what I could do better or have I done certain things right". These students displayed some concerning mental health issues related to their lack of success or misunderstandings of learning processes, particularly associated with online learning expectations. Similarly, another participant explained his learned ability to concentrate deeply was because of his cognitive behavior therapy and mindfulness strategies to treat his anxiety, stating "I do a lot of meditation". This treatment enabled him to experience improved behavioral engagement through better focus and ability to pay more attention to his learning which provided a more positive learning experience for him. However, this excessive attention on managing his thoughts inhibited the flow experience due to the excessive regulation of thoughts, limiting his ability to lose himself in the task, much like the over-thinkers.

Lack of Social Presence

In this study, lack of social presence, in the form of supportive relationships, represented a key inhibitor to flow. Participants who did not experience flow predominantly conveyed their lack of interest in, or any need to, interact and form relationships with their peers, stating "I really try to talk to them the minimum possible". Interestingly, while this

participant expressed his desire for critical discussion and problem solving with others, he stated he was not interested in interacting with his peers online, reflecting his lack of willingness to communicate differently in the online learning environment, despite previous success and enjoyment from this in his first degree when he learned face to face. These non-flow participants also reported fewer online interactions in general with their peers attributed to several reasons. One participant said it was due to their introverted personality, but other participants reported they experienced anxiety at the thought of interacting with anyone on the LMS, reporting *"*fear of appearing stupid*"* as a major contributor. Some participants showed little interest in forming relationships with their peers and felt like it brought no benefit to their learning, stating "it just wouldn't benefit me in any way I think".

The findings did not indicate that students learning with their peers influenced flow experiences but instead contributed to their emotional and cognitive engagement and sense of belonging to an academic community of support. One participant stated that "working with another student and having to explain where you are coming from and compromise and listen to their ideas and stuff, I found hugely valuable". Another element of support found among flow participants was social and emotional support from family members with experience at university, or work colleagues who typically worked in the education industry. One participant remarked that "thinking about how excited I have been to tell colleagues what I've learned" and "if you don't have access to teachers or other people doing postgrad work, I don't know how you'd get through it". Interestingly, however, among non-flow participants, these supportive relationships with others outside the formal academic community were absent, and many of these students appeared to lack enjoyment and purpose from their learning.

Lack of Interest and Prior Experience

Participants who experienced flow in this study were interested in the content they were learning and spent more time and attention on activities, which facilitated flow experiences. Lack of interest in the content was a major inhibitor to flow, with participants reporting "it's not something that I'm super intrigued about" and "interest in the subject is a major influence. I procrastinate more when it's something I may not, in particular, enjoy as much". This lack of interest in their content deeply affected the participants' ability to enjoy learning and limited their behavioral engagement. However, other factors also contributed to their lack of interest. Participants who displayed interest in their learning and experienced flow had prior knowledge and experiences in a professional education setting, which made them feel personally connected to what they were studying. Some participants already held roles in schools, and this brought additional relevance to their learning; as one reported, *"*I'm reading that for my own benefit and applying it to the things that happen in my classroom*"*. Paradoxically, all the participants who did not experience flow also did not have any prior knowledge and experience in professional education settings and, in fact, displayed many negative preconceived ideas about the content of their learning. This ultimately appears to have influenced participants' closed mindset, lack of motivation, interest, personal connection to their studies, behavioral engagement, and flow experiences (Kumasaka, 2024).

Discussion

The finding in this study related to lack of time aligns with Csikszentmihalyi's (2008) research, who reported that time is one of the most commonly mentioned components of flow among those who experience it. When time is dedicated to an activity, deep involvement is encouraged, resulting in concentration and flow. Adversely, if one does not have enough time,

flow is inhibited. Online learners are mostly non-traditional mature-aged students, and usually their family and work commitments are greater than on-campus students', which effects the time available for study (Greenland & Moore, 2014; Ragusa & Crampton, 2017). Not surprisingly, these students must balance multiple roles and tasks and are often very time poor. Xavier and Meneses (2022) reported that time was a significant challenge to higher education students studying online, and Veletsianos et al. (2021) found that students needed to be more realistic with time commitments required to be successful when studying online. These same findings were confirmed as an inhibitor to flow in this study and highlights the significance of educating students on the importance of study techniques and realistic time requirements.

Csikszentmihalyi (2008) found that the ability to resist distractions encourages deep concentration and can focus attention, which enables flow. The finding in this study of students' inability to resist distractions highlights the paradox that technology has brought with it and the implications for inhibiting flow. Digital technologies offer many students the flexibility of online learning but also bring many distractions. Meishar-Tal et al. (2022) found that mobile phones, among other digital and environmental distractions, were the most common distractions to higher education students. These findings reflect the need to assist and educate online students, particularly in their first year of study, about how to manage the distractions that technology brings and support them in learning how to focus their attention on the learning task and develop good study habits early. Mrazek et al. (2012) found that mindfulness training can reduce mind-wandering behaviors. However, mindfulness requires significant regulation of attention to focus on the techniques, which inhibits the flow experience (Csikszentmihalyi, 2008; Csikszentmihalyi & Nakamura, 2010) therefore, other strategies to focus attention should be encouraged. Often, higher education online learning providers have an expectation that students will be able to learn appropriate strategies to study for themselves and that high levels of engagement, such as flow, will occur. This highlights the need for higher education providers to assist students in learning appropriate study techniques and educating them on strategies that will assist with task focus and resistance to distractions.

Some participants who experienced non-flow in this study reflected common characteristics of overthinkers. Interestingly, participants who showed overthinking tendencies (an inhibitor to flow), were mature age women. Studies have confirmed that mature age women students are more likely to experience identity struggles, as they find a fit between their roles and commitments, often resulting in anxiety and tension (Edwards, 1993; Moss, 2004; Stone & O'Shea, 2019b). Constant worry about doing something wrong or how others will perceive them indicates a lack of flexible thinking, behavior, and of an autotelic personality which, in this study, caused lack of confidence and mental health concerns for women. Csikszentmihalyi (2008, p. 85) described this type of personality as typical of someone who uses too much energy and thinking of self, as having "excessive self-consciousness". Further, people with this personality type cannot easily enter flow or experience deep enjoyment, when attention is too rigid and tight. This not only impedes flow but also prevents personal growth, making learning more difficult. This finding is a significant reason for further research into fostering better psychological supports for women as they enter higher education, particularly as mature students.

Similarly, cognitive behavior therapy and mindfulness strategies also reflected an impediment to flow. During use of these strategies, constant monitoring of thoughts is required and this "excessive regulation" of the conscious mind, prevented focused attention on the task. Like the overthinkers, when thoughts are constantly monitored and too rigid, it

prevented loss of self during the activity (Csikszentmihalyi, 2008, p. 85). While one participant experienced deeper cognitive engagement with learning, excessive regulation of thought limited opportunities for flow and associated growth. Despite increasing student use of mindfulness techniques intended to assist with focus and learning, the findings in this study contradict this strategy and encourages alternative techniques which do not require excessive thought, such as breathing techniques, to improve attention and cognitive engagement leading to opportunities for flow. These findings also reflect that mental flexibility facilitates flow experiences, although this may not be an option for some individuals, as certain personality traits are inherited and some people lack the suitable cognitive flexibility and openness which flow requires (Csikszentmihalyi, 2008; Kashdan & Rottenberg, 2010).

The isolation and frustration of online learners due to the inherent lack of social interactions and presence in this environment is often reported (Lambrinidis, 2014; Sung & Mayer, 2012) along with the challenges of developing social and emotional relationships for support (Garrison, 2007). Research on presence in education has reported the importance of social relationships to learning (Garrison, 2003, 2007; Glazier, 2016; Jones, 2010; Robinson et al., 2017). Previous research has described the challenges of forming social and emotional relationships for support in the online learning environment and how the face-to-face learning environment provides better opportunities for this (Garrison, 2007). Recent research has focused on the use of synchronous video communication and how telepresence brings the feeling of physical presence to online environments, which can influence flow experiences (Guo et al., 2016). This was contradicted in the current study; while telepresence influenced emotional engagement through positive online interactions between instructor and student, it did not influence the flow experience. The findings in this study reflect the need for supportive relationships for emotional and cognitive engagement but also highlighted diverse student needs and revealed that students who desired positive working relationships with their peers to support engagement would seek them out from a variety of sources, such as peers, family, and colleagues working in industry. The findings also identified that while peer-to-peer relationships positively influence emotional engagement, they do not influence flow, highlighting a tension for educators in higher education: encouraging positive relationships between peers may be helpful but limited.

A new finding from this study reflects students' need for supportive relationships from knowledgeable others outside the formal academic community to foster emotional engagement and flow. This supportive relationship could be with someone from the education industry or someone with prior experience in higher education. Stone and O'Shea (2019b) recognised that since most online students are mature age and often first in the family to participate in higher education, many students may not have access to others with higher education experience. Often, these students have higher expectations of support from within the formal learning environment, such as the instructor, and do not look elsewhere for academic supports (Ragusa & Crampton, 2017). However, when supportive relationships were absent, participants did not experience flow which, at times, led to limited behavioral and cognitive engagement and even stress and poor mental health in some students. Future higher education students in online environments could be encouraged to establish a support network with people outside of the formal learning environment who may be able to relate to the content or their experiences. In addition, these supportive relationships should be able to do more than just provide social and emotional support, but also encourage confidence in students to discuss, clarify, and reflect on learning via face-to-face interactions, nurturing

intellectual curiosity and self-efficacy and facilitate positive experiences towards learning.

A key finding related to interest and prior experience in education and its influence on flow suggests this could be an under-researched area in this context. Studies of prior experience and effect on flow have been limited to online gaming (Cowley et al., 2019; Palomaki et al., 2021) but show that increased experience with an activity improves learning and enhances flow. Cognitive psychology has recognised the influence of prior experiences on learning and research on information-processing theory suggests that students direct more attention to learning when it fits with prior knowledge (Knowles et al., 2020). This was reflected in the current study when those who experienced flow appeared better able to direct their attention, connect their learning with prior experiences, and nurture interest than those who lacked any prior knowledge nor experience in education. Those participants who appeared less interested directed less attention to their learning, resulting in fewer opportunities for flow or no flow at all. For many of these participants, this led both to reduced engagement and less learning enjoyment; in some cases, students questioned the meaning of a course and related learning. It seems that participants who lacked interest or knowledge of the education industry lacked purpose and meaning, resulting in confusion, apathy, or, at times, stress.

Participants in this study who did not experience flow displayed not only reduced interest but also lacked personal connection and meaning to their studies. This could be attributed to their lack of prior experience and knowledge of education, as the flow participants reported these factors as contributing to their success, attributing a perceived advantage over other students to their current roles in educational settings. Non-flow participants had no prior experience in the education industry. The postgraduate participants, although they had prior experience in other diverse industries, such as business and medicine, this influenced their perceptions of education, some negatively. Preconceived ideas about the education industry and lack of experience with it negatively influenced behavioral engagement and affected how immersed or involved in their learning they could become. The role of experience in an industry prior to enrolment in the relevant course of study is a new finding which could have wide ranging implications for higher education institutions. While it is unlikely that prior experience in industry can be mandated for enrolment in a course, higher education providers could do more to ensure that courses are connected to industry and provide not only learning experiences that replicate authentic industry work but also encourage students to volunteer in industry related fields to gain valuable experience. This could nurture students' interest in their chosen field and foster relationships for student support from knowledgeable others, resulting in greater success in their course, improving behavioral engagement and more flow experiences.

Conclusions and Recommendations

There is no doubt that with the increasing landscape of online learning in higher education and the rapid development of technology, the conundrum of technology deepens. Technology is the tool online students must use to learn but is the very same distraction that will remove any chance of flow. Higher education institutions could do more to improve student education around realistic expectations for online learning (Jefferies & Hyde, 2010; Ragusa & Crampton, 2017). This could involve providing modules that talk about appropriate environments for study and time required for effective learning, deep engagement, and flow. In addition, educate students on the importance of managing distractions from mobile phones, social media, and family.

Furthermore, higher education institutions could create more units, particularly in students' first year of study, which include the importance of appropriate study techniques, the importance of focusing attention on learning tasks, and strategies to achieve focused attention, such as breathing techniques and yoga which research reported as influencing attention and improved cognitive responses (Ma et al., 2017; Velikonja et al., 2010). These units could also ensure students learn about access to databases and free resources, as this was identified as having importance to both online learners (Anderson & Cuttler, 2020) and flow. (Kumasaka, 2024). These study technique units should be delivered throughout the course to reinforce the notion that study techniques are intrinsic to their degree and important to develop since they foster flow throughout their courses of study.

Another key finding highlights the importance of relationships outside the class itself since an emotionally engaged support network can enhance learning. If students do not have access to knowledgeable others in an education-related professional setting, they could consider developing a trusting relationship with a mentor teacher during professional experience placements or become involved in a mentoring program, if available. Students should be encouraged to form supportive relationships with peers outside of the formal learning context and become involved in peer support programs if available, as student success with these programs has been reported (Horvath et al., 2019). These could include final year students mentoring first year students and the possibility of cross-institutional mentoring.

New findings from this study suggest that higher education providers could also offer experiences in the education industry to their students to nurture interest. Strategies could be adopted, such as encouraging students to volunteer their time in a professional setting, particularly if they lack prior experience or involvement in the education industry upon enrolment in their course. This could provide an authentic environment for students to experience, increase student interest and investment in their field and create opportunities for supportive relationships to develop. This could improve students' connection to their learning, which may improve self-efficacy, foster motivation, and expand engagement and flow experiences.

This study has proposed several actions that could be undertaken by higher education providers and students, summarised in Table 1. Further research is needed to explore the impact of these actions on student flow experiences across various fields of study and disciplines, particularly those without embedded professional or industry placements. Future research could also include longitudinal studies of tracking flow experiences across the duration of students' studies and the impact this may have on learning outcomes and retention across diverse programs.

Table 1

A Summary of the Barriers to Flow and the Implications to Education Providers and Students

Barriers to flow	**Implications**
Overthinking and excessive thought regulation strategies	Institutions should create courses with psychological safety as a key consideration. Students should consider mindfulness and self-monitoring strategies carefully and their placement in courses.

Time	Institutions could provide specific modules in first year of courses, which educate students on the time required for effective learning.
Distractions such as family and technology	Institutions could provide modules on study techniques and how to focus attention, such as breathing and yoga.
Relationships for support from 3 sources: - education industry colleagues - family members - peers	Program leaders could educate and foster student development of these relationships through: - mentor teachers from professional experience placement - mentoring programs - peer support programs
Interest in the content	Instructors and Program leaders could provide strategies to students to encourage interest and gain experience in the school setting, by volunteering at a school and personalising content.
Prior experience in education industry	Program leaders encourage strategies for students to gain experience such as volunteer in a professional setting.

Limitations

There were several limitations identified that may have impacted the research. One issue may be the limited interview data collected which cannot be generalised. Interviews were voluntary, and this could have limited the diversity in responses. The researchers attempted to mitigate any bias by interviewing four undergraduate (two males and two females) and four postgraduate (one male and three females) participants who had volunteered and provided consent. Ultimately, this was largely dependent on participant availability and willingness to volunteer. This could be a limitation in a traditional research sample; however, the hermeneutic phenomenological approach is not concerned with aspects of an individual but is more focused on the experiences of the individual with the phenomenon, which partially mitigates this limitation.

Another limitation is that since data were collected, the use of artificial intelligence (AI) has saturated the higher education sector. While AI offers many enticing benefits, it also brings with it many challenges to engagement, assessment, and task design (Wang, 2023). As flow relies on many different variables, the use of AI in learning is unlikely to have affected the flow experience, as it offers no skill-challenge task, a requirement of flow. Although it is possible that AI could have altered the number of participants in this study, it is unlikely to have affected the quality of the flow experiences during the study. Equally, it would be interesting for future research to reexamine flow in the online learning environment and its influence on behavioral, emotional, and cognitive engagement, due to this change.

Summary

This study sought to explore multi-layered engagement in online higher education students through the lens of flow. Flow experiences have the potential to improve online

student experience and outcomes in higher education contexts, in addition to improving student well-being (Csikszentmihalyi, 2014). Consequently, the application of flow theory to this study through a phenomenological approach had significant findings for researchers of flow theory, the higher education institutions and online students. Additionally, this study enriched the understanding of human experiences with non-flow in the online learning context and provided academic and practical insights for researchers and educators in this field.

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. This study was approved by Curtin University Human Ethics Approval # HRE2019-0155.

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Conflicts of Interest

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

AI Use

No generative artificial intelligence was used in the preparation of this manuscript nor in the research project.

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What Drives Generation Z Pre-Service Teachers' Acceptance of ChatGPT-assisted Teaching Practicum? The Roles of Enjoyment and Trust

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Abstract
The growing presence of generative AI (GenAI) tools such as ChatGPT is reshaping teacher education, yet there is still limited empirical attention to the emotional and relational aspects that shape their willingness to adopt. This study extends the Technology Acceptance Model (TAM) by incorporating perceived enjoyment and trust to examine how Generation Z pre-service teachers (PSTs) in Indonesia accept and use ChatGPT-assisted teaching practicums. A survey involving 445 participants was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. The results reveal that perceived enjoyment significantly predicts both perceived usefulness and perceived ease of use, while trust primarily affects perceived usefulness. Moreover, perceived enjoyment, trust, and perceived usefulness significantly shape Generation Z PSTs' attitudes toward ChatGPT, which subsequently predict their intention to use it. Interestingly, trust does not significantly influence perceived ease of use, and perceived ease of use shows no direct effect on attitude. The extended model explains 60.2% of the variance in perceived usefulness, 46.0% in perceived ease of use, 49.0% in attitude, and 45.6% in intention to use, indicating moderate explanatory power. These results demonstrate that affective and relational dimensions significantly shape how pre-service teachers embrace ChatGPT, offering practical insights for the design of AI-supported practicum models that encourage ethical awareness, emotional engagement, and the long-term advancement of pedagogical innovation.

Keywords: ChatGPT; Generation Z; pre-service teachers, Technology Acceptance Model, teaching practicum

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Generative artificial intelligence (GenAI) tools such ChatGPT are transforming teacher education globally. As an intelligent instruction assistant, ChatGPT supports pre-service teachers (PSTs) manage multiple aspects of lesson preparation, classroom interaction, and student assessment (Bae et al., 2024; Ihsanurrahmah et al., 2025; Kusuma et al., 2024; Lee & Zhai, 2024). Through their capacity to generate teaching materials, simulate pedagogical dialogues, and offer instant feedback (Adam et al., 2025; Barbieri & Nguyen, 2025; Gamlem et al., 2025; Kusuma et al., 2024), ChatGPT helps reduce cognitive demands and enhance pedagogical reflection, particularly during teaching practicums that demand adaptive decision-making and emotional regulation (Daud et al., 2025; Wulandari & Purnamaningwulan, 2024). Yet, its effectiveness depends not only availability of technology but also on PSTs' readiness to use it responsibly, creatively, and ethically within authentic instructional contexts. For Generation Z PSTs, born between 1997 and 2012, who are immersed in technology-rich environments, ChatGPT offers new opportunities for pedagogical innovation but also exposes a persistent gap between digital fluency and pedagogical competence (Lucas et al., 2025). Although many of these teachers are technologically proficient, they often lack the pedagogical insight and ethical awareness required for the responsible integration of ChatGPT into classroom practice (Bae et al., 2024). This imbalance between technological competence and pedagogical readiness underscores the need to examine the psychological and motivational factors influencing Generation Z PSTs' acceptance and use of ChatGPT in real classroom settings, particularly within developing regions such as Indonesia.

In Indonesia, the adoption of GenAI like ChatGPT into higher education is part of the government's broader initiative to accelerate digital transformation. This initiative is regulated by the Ministerial Regulation on Higher Education, Science, and Technology No. 39 of 2025 concerning Higher Education Quality Assurance, which emphasizes technology-enhanced learning and comprehensive quality assurance reforms. The regulation establishes a national framework that promotes adaptability to scientific and technological advancements, strengthens institutional accountability through internal quality assurance systems, and encourages flexibility in the delivery of learning. It further emphasizes the need to embed innovative digital tools and instructional technologies, such as ChatGPT, within teacher education curricula to support ongoing quality enhancement and reflective teaching practice. This policy aligns with Indonesia's vision of developing digitally skilled and globally competitive educators capable of navigating AI-supported learning environments. However, these policy initiatives do not automatically translate into effective classroom implementation. Achieving the intended outcomes remains a complex process that depends not only on infrastructural readiness but also on PSTs' psychological preparedness to adopt and internalize technologies such as ChatGPT as integral components of their professional identities and pedagogical practices.

Despite these progressive initiatives, empirical research continues to reveal persistent inequalities in digital access, infrastructure, and institutional guidance on the pedagogical and ethical use of emerging technologies (Sanusi et al., 2024). These disparities suggest that although the national digitalization framework provides overall direction for educational reform, its implementation remains inconsistent across regions and institutions. As a result, many PSTs, while confident in using digital tools, still struggle to align their use of ChatGPT with curricular

objectives and assessment standards. This challenge becomes particularly evident during the teaching practicum, which represents the capstone phase of teacher preparation in which PSTs must translate theoretical knowledge into effective classroom practice under supervision. While ChatGPT has been introduced to assist in practicum activities, its use also presents several pedagogical and ethical challenges. Studies have reported concerns about factual inaccuracies, the generation of biased or culturally inappropriate content, data privacy issues, and students' excessive dependence on AI-generated outputs, which may impede the development of critical and reflective thinking skills (Cacho, 2024; Sarwanti et al., 2024). These risks highlight the importance of developing teacher education programs that foster not only technological competence but also AI literacy, ethical sensitivity, and reflective judgment among PSTs. Consequently, Indonesia represents an important context for examining both the opportunities and challenges of ChatGPT-assisted practicum teaching in the Global South, where infrastructural readiness and cultural attitudes toward AI adoption differ markedly from Western contexts. Accordingly, this study seeks to identify the factors that shape PSTs' acceptance and use of ChatGPT in teacher education.

This study adopts the Technology Acceptance Model (TAM) as its theoretical foundation to investigate Generation Z PSTs' acceptance and use of ChatGPT-assisted practicum teaching in teacher education. Although TAM has long served as a robust framework for explaining users' behavioral intentions toward technology adoption, it primarily emphasizes cognitive and utilitarian factors while overlooking affective and relational dimensions that shape user engagement (Granić & Marangunić, 2019). This limitation restricts TAM's explanatory power in contexts where emotional involvement and interpersonal trust play an essential role, particularly in interactions involving ChatGPT. Unlike traditional educational technologies, ChatGPT generates autonomous and context-sensitive responses that simulate human conversation. Its interactive nature often evokes emotional reactions such as curiosity, enjoyment, and anxiety, while simultaneously requiring users to develop trust in the system's accuracy, reliability, and ethical behavior (Albayati, 2024; Polyportis & Pahos, 2024). Therefore, ChatGPT serves not only as a cognitive aid but also as an emotionally and socially interactive learning partner. To address these theoretical limitations, this study extends TAM by incorporating affective and relational constructs, specifically perceived enjoyment (PEJ) and trust (TR), to examine Generation Z PSTs' acceptance and use of ChatGPT-assisted practicum teaching. The study specifically aims to: (1) examine the influence of PEJ and TR on perceived usefulness (PU) and perceived ease of use (PEOU); (2) explore the effects of PEJ, TR, PU, and PEOU on PSTs' attitudes (ATT) toward ChatGPT; and (3) assess how ATT toward ChatGPT shapes their intention to use ChatGPT (IUC) in ChatGPT-assisted teaching practicum. Accordingly, the study addresses the following research questions:

1. How do PEJ and TR affect PU and PEOU in Generation Z PSTs' acceptance and use of ChatGPT-assisted teaching practicum?
2. What roles do PEJ, TR, PU, and PEOU play in shaping Generation Z PSTs' ATT toward ChatGPT-assisted teaching practicum?
3. To what extent does ATT toward ChatGPT influence Generation Z PSTs' IUC in ChatGPT-assisted teaching practicum?

By addressing these questions through a robust PLS-SEM analytical approach and a sample of 445 PSTs in Indonesia, this study provides timely insights into the cognitive, emotional, and relational factors that shape ChatGPT acceptance. The results contribute both theoretically and practically to advancing the understanding of technology acceptance in teacher education. Theoretically, this study extends TAM by incorporating emotional and relational factors, thereby enhancing its explanatory power in ChatGPT-mediated learning contexts. By integrating affective and relational-based constructs, the model offers a more comprehensive framework for understanding how Generation Z PSTs accept and use ChatGPT-assisted teaching practicum. Practically, the results provide valuable implications for policymakers and teacher educators in designing ChatGPT-integrated teacher education programs that are pedagogically sound, ethically informed, and emotionally engaging. These results underscore the importance of embedding AI-supported learning experiences that not only promote technological innovation but also cultivate ethical sensitivity, emotional engagement, and reflective professional growth among PSTs.

Literature Review

TAM

Davis (1989) established TAM to illustrate how user perceptions translate into decisions about adopting and using technological innovations, proposing that perceived usefulness (PU) and perceived ease of use (PEOU) are the primary determinants influencing users' attitudes and subsequent behavioral intention. Since its introduction, TAM has become one of the most widely applied models in technology-adoption and information systems research. However, the original version of TAM (TAM1) has been criticized for its limited focus on cognitive and functional beliefs while neglecting affective, contextual, and social factors that significantly influence technology use in educational environments (Granić & Marangunić, 2019). To address these limitations, subsequent extensions of the model, TAM2 and TAM3, introduced additional variables such as perceived enjoyment (PEJ), computer anxiety, trust (TR), facilitating conditions, perceived risk, and subjective norm (Padilla-Meléndez et al., 2012). The theoretical progression highlights that acceptance is no longer viewed as a purely cognitive process, but rather one shaped by affective reactions and social conditions.

Empirical studies have further validated these extensions across various technological contexts. For instance, Rahman et al. (2023) integrated PEJ and personal innovativeness to investigate how students form attitudes toward ChatGPT, demonstrating that cognitive and informational factors play a crucial role in shaping students' attitudes toward ChatGPT adoption. In another study, Al-Adwan et al. (2023) added personal innovativeness in IT, self-efficacy, perceived cyber risks, and PEJ to examine students' behavioral intentions toward the metaverse, emphasizing that PU, PEJ, and personal innovativeness in IT significantly enhance students' adoption intentions. Consistent with these results, Han (2024) analyzed Chinese medical undergraduates' use of intelligent tutoring systems by incorporating PEJ, self-efficacy, computer anxiety, social influence, and prior experience into TAM, confirming that emotional, psychological, and experiential factors strengthen technology acceptance. Albayati (2024) also expended TAM by adding privacy, self-efficacy, social influence, and TR to explore

undergraduate students' acceptance of ChatGPT, showing that ATT and TR are key predictors of behavioral intention, while privacy and security indirectly support adoption through PU and TR. In the e-learning context, Sasongko et al. (2025) integrated PEJ, perceived risk, perceived compatibility, and perceived self-efficacy, revealing that PEJ and self-efficacy significantly enhance students' acceptance of e-learning. Similarly, Fitriati et al. (2025) incorporated PEJ and self-efficacy into TAM to examine students' adoption of mobile learning, showing that PEJ and self-efficacy significantly drive students' current and continued use of mobile learning.

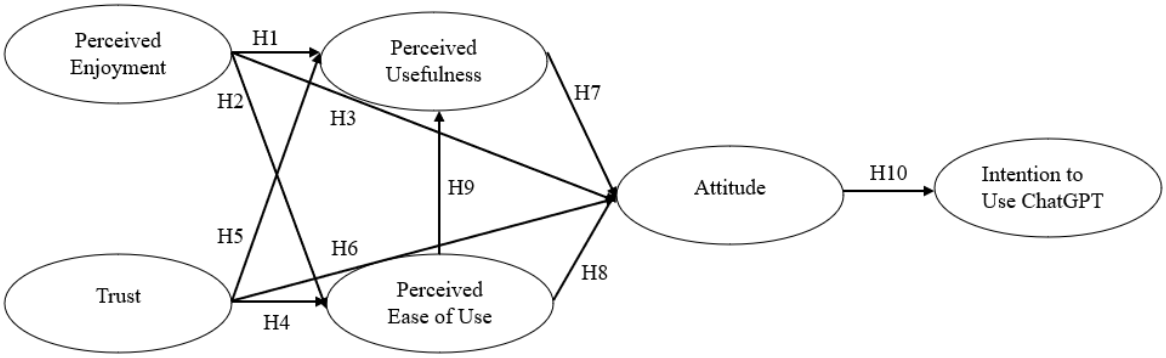
Collectively, these studies demonstrate the theoretical evolution of TAM from a predominantly cognitive framework to a multidimensional model that integrates affective, relational, and contextual factors, thereby enhancing its explanatory power in technology-mediated and AI-supported learning environments. Despite these advancements, many TAM extensions remain concentrated on functional and environmental aspects, providing limited insight into the affective and ethical dimensions that shape users' interactions with intelligent systems. Consequently, emotional engagement and ethical assurance remain underexplored in TAM-based studies, particularly in the context of ChatGPT-assisted teacher education. Therefore, this study extends TAM by incorporating PEJ and TR to provide a more comprehensive explanation of how Generation Z PSTs adopt and utilize ChatGPT-assisted teaching practicum. Integrating these constructs broadens TAM's explanatory scope beyond rational evaluation, offering a more human-centered understanding of technology acceptance that includes emotional and ethical considerations. Drawing on these theoretical insights, the subsequent section introduces the proposed model and hypotheses, which in turn determine the methodological strategy used to validate the model.

Proposed Model and Hypothesis Development

Drawing on the theoretical insights in the literature review, this study extends the original TAM by adding PEJ and TR with the core constructs PU, PEOU and ATT, and intention to use ChatGPT (IUC). This enhanced framework provides a more holistic understanding of the factors that influence Generation Z PSTs' adoption of ChatGPT-assisted teaching practicum. The relationships among these constructs are illustrated in Figure 1, which acts as the guiding framework for hypothesis development and the overall research design.

Figure 1

The Proposed Model



Perceived enjoyment.

Venkatesh (2000) describes PEJ as a user's feeling of enjoyment that arises purely from interacting with a system, separate from any expectation of better performance outcomes. Grounded in intrinsic motivation theory (Ryan & Deci, 2000), it reflects users' internal drive to engage with a system simply because they find it interesting and rewarding. This concept captures the hedonic dimension of technology use, emphasizing how enjoyable or stimulating users perceive their interaction to be (Venkatesh et al., 2012). Within the extended TAM, PEJ consistently been shown to influence users' PU and PEOU of new technology, such as the metaverse (Wu & Yu, 2024), online education platforms (Adouani & Khenissi, 2024), mobile learning (Fitriati et al., 2025), and GenAI (Cano & Nunez, 2024; Han, 2024; Octavia & Nugraha, 2024). Moreover, PEJ contributes to shaping users' ATT toward adopting new technologies (Sabbir et al., 2020). On this basis, the following hypotheses are formulated:

H1: PEJ positively shapes Generation Z PSTs' PU of ChatGPT.

H2: PEJ positively shapes Generation Z PSTs' PEOU of ChatGPT.

H3: PEJ positively shapes Generation Z PSTs' ATT toward ChatGPT.

Trust

TR refers to users' belief that a technological system is dependable, competent, and ethically developed to safeguard their interests (Chavoshi & Hamidi, 2019). It serves as a critical psychological element that shapes individuals' readiness to adopt and rely on new technologies, particularly among younger users (Albayati, 2024). Existing studies have shown that TR significantly influences users' PU and PEOU in artificial intelligence applications (Al Shamsi et al., 2022; Alzboon et al., 2025; Octavia & Nugraha, 2024). TR has also been identified as a determinant that shapes users' ATT toward technology adoption (Albayati, 2024; Alzboon et al., 2025; Polyportis & Pahos, 2024). Therefore, the following hypotheses are put forward:

H4: TR positively shapes Generation Z PSTs' PU of ChatGPT.

H5: TR positively shapes Generation Z PSTs' PEOU of ChatGPT.

H6: TR positively shapes Generation Z PSTs' ATT toward ChatGPT.

Perceived usefulness.

Davis (1989) defines PU as the perception that a technology enhances task effectiveness. Within TAM, this perception plays a decisive role in forming users' ATT toward adopting the technology. Research consistently highlights that individuals' PU are predictors of their willingness to adopt new technologies across diverse fields, including digital learning tools (Ly & Doeur, 2024; Sayaf et al., 2022), translation technologies (Li et al., 2024), and ChatGPT (Aguilos & Fuchs, 2024; Geddam et al., 2024; Liu & Ma, 2024; Tiwari & Bhat, 2024). Accordingly, the following hypothesis is formulated:

H7: PU positively shapes Generation Z PSTs' ATT toward ChatGPT.

Perceived ease of use.

PEOU is conceptualized as users' perception that a technology can be operated smoothly and without substantial cognitive load (Davis, 1989). Within the TAM framework, PEOU exerts a significant influence on shaping users' ATT toward technology adoption (Venkatesh & Bala, 2008). Research has shown that PEOU significantly predicts ATT toward adopting various technologies, including digital learning tools, translation applications, the metaverse, and GenAI platforms such as ChatGPT (Aguilos & Fuchs, 2024; Alejandro et al., 2024; Geddam et al., 2024; Li et al., 2024; Sayaf et al., 2022; Wu & Yu, 2024). Moreover, PEOU has been found to influence PU (Alejandro et al., 2024; Almogren et al., 2024; Al Shamsi et al., 2022; Kılıç et al., 2025; Sun et al., 2025; Wu & Yu, 2024; Zhang et al., 2023; Zhang et al., 2026). Drawing from the findings above, the following hypotheses are formulated.

H8: PEOU positively shapes Generation Z PSTs' ATT toward ChatGPT.

H9: PEOU positively shapes Generation Z PSTs' PU of ChatGPT.

Attitude and intention to use ChatGPT.

ATT defines an individual's evaluative judgment of whether adopting a given technology is beneficial or undesirable (Ajzen & Fishbein, 1975). As noted by Benoit et al. (2009), ATT serves as a critical determinant of users' behavioral intentions to adopt technological innovations. A substantial body of research has shown that ATT plays a decisive role in predicting users' intentions to engage with various forms of technology, including online learning platforms (Sayaf et al., 2022), metaverse-based applications (Wu & Yu, 2024), translation systems (Li et al., 2024), and GenAI tools such as ChatGPT (Alejandro et al., 2024; Dahri et al., 2024; Liu & Ma, 2024; Sun et al., 2025; Wu et al., 2024). Informed by this evidence, the following hypothesis is formulated:

H10: ATT positively shapes Generation Z PSTs' IUC.

Methods

Participants

This study employed a quantitative cross-sectional design, collecting data through a self-administered questionnaire completed by PSTs who were recruited using a convenience sampling technique. A total of 445 Generation Z PSTs enrolled in teacher education programs at public universities in Indonesia completed the instrument, and all responses were considered valid for analysis. Among the participants, 53.9% were female and 46.1% were male. Most participants (83.4%) were aged 17–20 years, while 16.6% were between 21 and 24 years of age. The PSTs were drawn from various academic programs, with the majority majoring in English education (30.6%), followed by Indonesian language education (25.2%), primary school education (20.4%), informatics engineering education (13.9%), and mathematics education (9.9%). Table 1 provides an overview of the participants' demographic profiles.

Table 1

Participants Demographics

Characteristic	Item	Number	Percentage
Sex	Male	205	46.1
	Female	240	53.9
Age	17–20	371	83.4
	21–24	74	16.6
Department	English education	136	30.6
	Indonesian language education	112	25.2
	Primary school education	91	20.4
	Mathematics education	44	9.9
	Informatics engineering education	62	13.9

Instruments

The online questionnaire used in this study consisted of two main parts. The first part collected background information from participants The second part captured the core constructs of the research model by adapting measurement items from previously validated instruments: PU and PEOU (Davis, 1989); PEJ (Davis et al., 1992); TR (Chong et al., 2012); ATT (Taylor & Todd, 1995); and IUC (Kordzadeh, 2019), as presented in Appendix A. Responses were collected on a 5-point Likert scale, with 1 denoting strong disagreement and 5 representing strong agreement. To ensure linguistic and cultural appropriateness for the Indonesian context, a back-translation procedure was applied. The instrument was initially translated from English to Indonesian by a bilingual specialist, after which a separate translator rendered it back into English to ensure both conceptual consistency and semantic accuracy.

A panel of three experts in educational technology and digital innovation evaluated the questionnaire to confirm that each item appropriately represented the intended constructs. Their

review focused on item clarity, contextual fit, and relevance to PSTs' use of ChatGPT during practicum activities such as planning lessons, creating instructional materials, and obtaining pedagogical support. Their feedback led to several revisions aimed at enhancing the questionnaire's alignment with the actual experiences and digital habits of PSTs. Following this review, a pilot test was administered to 30 PSTs with characteristics comparable to the target sample. This preliminary phase aimed to detect unclear items and evaluate the initial reliability of the instrument. Participants were asked to complete the online questionnaire and share their impressions regarding the clarity, suitability, and ease of understanding of the items, particularly those addressing their use of ChatGPT during practicum activities. Insights from the pilot resulted in minor refinements to improve the instrument's readability and contextual fit for use in the main study.

Data Collection

The survey was administered online from August 4 to September 28, 2024. The intended participants were Generation Z PSTs studying at private universities located in Central Java, Indonesia. To maximize accessibility and response rates, the survey link was shared through WhatsApp Groups, a platform frequently used by students for academic discussions and coordination. To determine eligibility, the first page of the survey included a screening question confirming prior exposure to ChatGPT. This filtering step was crucial to ensure the relevance of the data to the study's focus, which centered on individuals with actual usage of the tool. Out of 460 collected responses, 15 were removed because the participants reported no previous experience with ChatGPT. Accordingly, 445 eligible responses were retained and analyzed in the final dataset.

Data Analysis

To address potential bias associated with collecting self-reported data from a single population, the study first evaluated common method bias (CMB). This was done through a full collinearity analysis in IBM SPSS 29, following the procedures recommended by Kock and Lynn (2012) and Kock (2015). The output confirmed that variance inflation values were within acceptable limits, indicating that CMB did not pose an issue in this dataset. Following the verification of data quality, the analysis advanced to the use of Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4 (Ringle et al., 2024). This method was selected due to its capacity to handle complex structural models and its suitability for datasets that do not follow a normal distribution, which is often the case in survey-based research (Chin et al., 2003). The analysis involved two sequential steps. First, the measurement model was assessed to examine the reliability and validity of the constructs. Next, the structural model was tested to evaluate the hypothesized relationships. Additionally, predictive relevance was examined using the PLS-Predict function in SmartPLS to enhance the practical interpretability of the findings.

Results

Common Method Bias

PLS-SEM was applied using SmartPLS 4 (Ringle et al., 2024) to examine both the measurement and structural models. This analytical technique was chosen because of its effectiveness in managing complex variable relationships and its robustness when dealing with non-normally distributed datasets, a frequent condition in questionnaire-based research (Chin et al., 2003). Since the data were obtained from a single respondent group, the study examined the possibility of Common Method Bias (CMB) before proceeding with the model evaluation. The assessment followed the full collinearity approach proposed by Kock and Lynn (2012) and Kock (2015), implemented in IBM SPSS 29. This procedure involved regressing all latent constructs against a common variable and reviewing the Variance Inflation Factor (VIF) scores. Values of 3.3 or lower were considered acceptable, indicating negligible CMB. The analysis revealed that all VIF values met this criterion (see Table 3), confirming that single-source bias was not a concern in the dataset.

Table 3

Full Collinearity Testing

Variable	PEJ	TR	PU	PEOU	ATT	IUC
VIF	2.475	1.302	2.595	2.765	2.225	2.512

Note. PEJ: Perceived Enjoyment, TR: Trust, PU: Perceived Usefulness, PEOU: Perceived Ease of Use, ATT: Attitude toward ChatGPT, IUC: Intention to Use ChatGPT.

Measurement Model

The evaluation of the measurement model followed the two-stage analytical procedure proposed by Anderson and Gerbing (1988). In the first stage, the measurement component of the model was examined to determine the reliability and validity of each construct, following the guidelines suggested by Hair et al. (2022). In the subsequent stage, the structural model was analyzed to explore the hypothesized links among the study variables.

To assess reliability, estimates of Cronbach's alpha and composite reliability (CR) were calculated. As shown in Table 4, the Cronbach's alpha coefficients ranged between 0.778 and 0.887, while the CR values were between 0.871 and 0.928. All values exceeded the recommended minimum of 0.70, indicating that the measurement items consistently represented their respective constructs. Convergent validity was assessed using factor loadings and the average variance extracted (AVE). All items showed loadings above 0.87, and AVE values fell between 0.641 and 0.812, both above the commonly accepted cutoff of 0.50. These findings demonstrate that the indicators adequately capture the underlying constructs and provide strong evidence of convergent validity.

Table 4

Measurement Model

Variables	Indicator	Mean	SD	Loadings	A	CR (rho c)	AVE
PEJ	PEJ1	0.902	0.013	0.902	0.884	0.928	0.812
	PEJ2	0.900	0.011	0.901			
	PEJ3	0.901	0.012	0.900			
TR	TR1	0.768	0.030	0.770	0.887	0.916	0.687
	TR2	0.841	0.019	0.842			
	TR3	0.827	0.026	0.830			
	TR4	0.844	0.022	0.846			
	TR5	0.852	0.019	0.853			
PU	PU1	0.848	0.016	0.848	0.845	0.895	0.681
	PU2	0.847	0.017	0.847			
	PU3	0.751	0.028	0.752			
	PU4	0.850	0.017	0.850			
PEOU	PEOU1	0.803	0.020	0.804	0.778	0.871	0.693
	PEOU3	0.871	0.014	0.871			
	PEOU4	0.820	0.020	0.820			
ATT	ATT1	0.799	0.021	0.799	0.816	0.877	0.641
	ATT2	0.793	0.029	0.794			
	ATT3	0.823	0.019	0.823			
	ATT4	0.784	0.030	0.786			
IUC	IUC1	0.891	0.012	0.891	0.827	0.896	0.743
	IUC2	0.850	0.018	0.851			
	IUC3	0.842	0.018	0.843			

Note. PEOU2 and PEOU5 were deleted due to low loadings.

Discriminant validity was evaluated using the Heterotrait–Monotrait ratio (HTMT), following methodological recommendations from prior research (Henseler et al., 2015; Franke & Sarstedt, 2019). Under these guidelines, HTMT values ≤0.85 indicate a strict level of discriminant validity, whereas values ≤0.90 are still acceptable under a more relaxed threshold. As shown in Table 5, all HTMT values were below 0.90, except for the construct of PU, which slightly exceeded the threshold. To further confirm discriminant validity, a bootstrapping test was carried out. The bias-corrected confidence intervals for all construct pairs did not include the value zero, indicating that each construct is statistically distinct from the others. Overall, these results support the conclusion that the measurement model is both valid and reliable.

Table 5

Discriminant Validity (HTMT)

Variables	PEJ	TR	PU	PEOU	ATT	IUC
PEJ						

TR	0.411				
PU	0.734	0.371			
PEOU	0.798	0.452	0.919		
ATT	0.728	0.527	0.636	0.694	
IUC	0.801	0.427	0.727	0.793	0.807

Structural Model

Following Hair et al. (2022), the structural model was evaluated by estimating path coefficients, t-values, and p-values through a bootstrapping process with 10,000 samples. To address Hahn and Ang's (2017) critique of overreliance on p-values, confidence intervals and effect sizes were also analyzed to enhance the rigor of hypothesis testing.

As summarized in Table 6, the results show that eight of the ten proposed hypotheses were supported. PEJ exerted significant positive effects on PU ($\beta = 0.252$, $p < 0.001$), PEOU ($\beta = 0.603$, $p < 0.001$), and ATT ($\beta = 0.376$, $p < 0.001$), thereby confirming H1, H2, and H3. Among these, the influence of PEJ on PEOU was the strongest, suggesting that enjoyment serves as a crucial affective driver of usability. This finding implies that when PSTs experience pleasure, curiosity, and satisfaction while using ChatGPT, they tend to perceive it as easier to operate and less cognitively demanding. The positive emotions derived from enjoyable interactions with ChatGPT enhance their confidence and willingness to engage with the tool, which subsequently strengthens perceptions of its usefulness and fosters a favorable attitude toward integrating it into practicum-based learning.

The results further indicate that TR positively predicts both PEOU ($\beta = 0.160$, $p = 0.002$) and ATT ($\beta = 0.218$, $p < 0.001$), thereby supporting H5 and H6. This suggests that when PSTs trust ChatGPT's reliability, security, and data protection mechanisms, they feel more confident and comfortable using it, which enhances both their PEOU and overall positive attitude toward the tool. However, TR did not significantly affect PU ($\beta = 0.028$, $p = 0.397$), leading to the rejection of H4. This indicates that although TR helps reduce uncertainty and encourages adoption, it does not directly influence PSTs' perceptions of ChatGPT's instrumental value for achieving teaching outcomes.

Furthermore, PU significantly shaped ATT ($\beta = 0.143$, $p = 0.024$), supporting H7, while PEOU strongly influenced PU ($\beta = 0.573$, $p < 0.001$), confirming H9. These results suggest that when Generation Z PSTs perceive ChatGPT as both useful and easy to use during their teaching practicum, they are more likely to develop positive attitudes toward its pedagogical application. However, PEOU did not show significant effect on ATT ($\beta = 0.129$, $p = 0.058$), leading to the rejection of H8. This indicates that ease of use alone may not be sufficient to foster positive attitudes unless accompanied by PU or emotional satisfaction. ATT was identified as the strongest predictor of IUC ($\beta = 0.676$, $p < 0.001$), providing strong support for H10. This highlights that Generation Z PSTs' positive attitudes play a decisive role in shaping their intention to continue using ChatGPT as a pedagogical assistant in future teaching practices.

The study further assessed the effect size (f^2) of each predictor to determine its relative contribution. Based on Cohen's (1988) criteria, f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects. As reported in Table 6, the largest effect was observed from ATT to IUC ($f^2 = 0.840$), indicating a substantial impact. This was followed by PEJ to PEOU ($f^2 = 0.581$) and PEOU to PU ($f^2 = 0.445$), both representing large effects. A moderate effect was found for PEJ to ATT ($f^2 = 0.139$), while smaller effects appeared for PEJ to PU ($f^2 = 0.087$), TR to ATT ($f^2 = 0.077$), and TR to PEOU ($f^2 = 0.041$). Minimal effects were noted for TR to PU ($f^2 = 0.002$), PEOU to ATT ($f^2 = 0.012$), and PU to ATT ($f^2 = 0.016$).

The explanatory strength of the model was assessed through the coefficient of determination (R^2). Based on the criteria outlined by Hair et al. (2014), values of 0.25, 0.50, and 0.75 correspond to low, moderate, and high predictive power. As illustrated in Figure 2, the R^2 values for the endogenous constructs were PU (0.602), PEOU (0.460), ATT (0.490), and IUC (0.456), indicating that the model demonstrates a moderate level of explanatory capability and successfully captures the cognitive, affective, and behavioral mechanisms that influence PSTs' engagement with ChatGPT.

Table 6

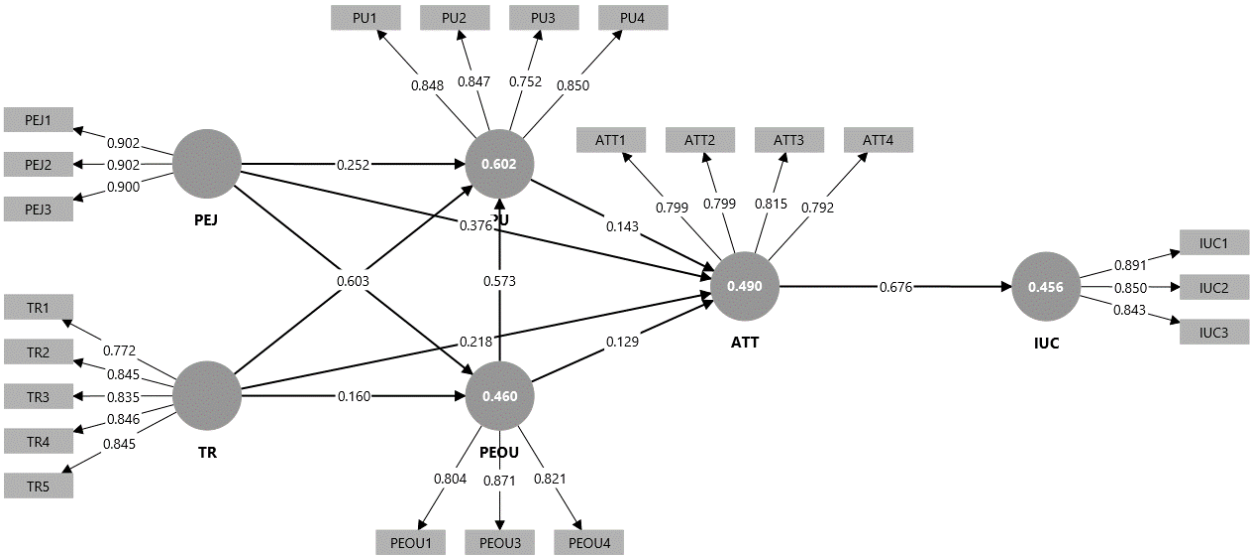
Hypothesis Testing

Hypothesis	Structural Path	Std. Beta	t-value	p-value	PCI LL	PCI UL	f^2	Decision
H1	PEJ → PU	0.252	5.158	0.000	0.161	0.352	0.087	Accepted
H2	PEJ → PEOU	0.603	13.814	0.000	0.513	0.684	0.581	Accepted
H3	PEJ → ATT	0.376	6.153	0.000	0.250	0.490	0.139	Accepted
H4	TR → PU	0.028	0.847	0.397	-0.034	0.095	0.002	Rejected
H5	TR → PEOU	0.160	3.162	0.002	0.064	0.261	0.041	Accepted
H6	TR → ATT	0.218	4.788	0.000	0.126	0.305	0.077	Accepted
H7	PU → ATT	0.143	2.256	0.024	0.019	0.268	0.016	Accepted
H8	PEOU → ATT	0.129	1.899	0.058	-0.004	0.264	0.012	Rejected
H9	PEOU → PU	0.573	10.863	0.000	0.463	0.671	0.445	Accepted
H10	ATT → IUC	0.676	19.746	0.000	0.606	0.741	0.840	Accepted

Note. A bootstrapping approach with 10,000 samples was employed to calculate the 95% confidence interval.

Figure 2

The Results of PLS-SEM



To evaluate the model's predictive performance, the PLSpredict procedure was applied in accordance with the guidelines of Shmueli et al. (2019). This approach employs a holdout sample and produces case-level predictions for both individual indicators and latent constructs through a 10-fold cross-validation process. As outlined by Shmueli et al., a PLS model is considered to have strong predictive power when its prediction errors are consistently smaller than those of a benchmark linear model (LM) or indicator average (IA). In contrast, if most errors are greater, the model lacks predictive ability, while a smaller proportion of higher errors suggests moderate or weak predictive strength. As shown in Table 7, all prediction errors from the PLS model were smaller than those from the linear benchmark, confirming that the model achieves high predictive accuracy.

Table 7

PLS-Predict

Indicators	Q^2predict	PLS-SEM_RMSE	LM_RMSE	IA_RMSE	PLS-LM	PLS-IA
PU1	0.330	0.604	0.601	0.738	0.003	-0.134
PU2	0.302	0.670	0.680	0.803	-0.010	-0.133
PU3	0.166	0.601	0.596	0.658	0.005	-0.057
PU4	0.318	0.655	0.660	0.793	-0.005	-0.138
PEOU1	0.309	0.620	0.631	0.745	-0.011	-0.125
PEOU3	0.305	0.684	0.697	0.820	-0.013	-0.136
PEOU4	0.320	0.707	0.724	0.857	-0.017	-0.150
ATT1	0.363	0.577	0.582	0.723	-0.005	-0.146

ATT2	0.203	0.725	0.728	0.811	-0.003	-0.086
ATT3	0.336	0.567	0.568	0.696	-0.001	-0.129
ATT4	0.214	0.718	0.710	0.810	0.008	-0.092
IUC1	0.332	0.604	0.590	0.739	0.014	-0.135
IUC2	0.290	0.552	0.533	0.655	0.019	-0.103
IUC3	0.302	0.634	0.624	0.760	0.010	-0.126

Discussion

This study investigates the determinants Generation Z PSTs acceptance and use of ChatGPT-assisted teaching practicum by extending TAM with two additional constructs: PEJ and TR to capture affective and relational dimensions of technology adoption. The results reveal that ATT had the strongest effect on IUC, indicating that Indonesian Generation Z PSTs' intention to adopt ChatGPT-assisted teaching practicum is driven predominantly by how positively they evaluate the technology. This is consistent with prior studies (Cano & Nunez, 2024; Dahri et al., 2024; Wu et al., 2024), which consistently highlights the pivotal role of ATT in shaping users' behavioral intentions. Similarly, Alejandro et al. (2024) and Sun et al. (2025) reported that PSTs who hold positive feelings toward ChatGPT are more likely to intend to integrate it into their lesson plans, highlighting how favorable attitudes translate into adoption intentions. The strong influence of ATT can be attributed to ChatGPT's ability to simplify core instructional tasks, including saving time in lesson plan preparation, assisting in the discovery and development of teaching materials, supporting more personalized learning experiences, and enabling data-informed analysis of student progress (Gamlem et al., 2025). These practical functions align with the expectations of Generation Z, who prefer digital tools that are efficient, intuitive, and capable of enhancing their workflow and learning outcomes. Therefore, ATT becomes the primary driver of adoption, as PSTs' positive evaluations of ChatGPT directly reinforce their intention to use it in teaching practicum activities.

PEJ also emerged as a strong predictor of PEOU. The strong effect of PEJ indicates that Generation Z PSTs perceive ChatGPT as easier to use when interactions are enjoyable and engaging, allowing them to focus on completing instructional tasks rather than on mastering the system. For Generation Z PSTs, who are familiar with intuitive and interactive digital tools, enjoyable interactions naturally increase perceived ease, making ChatGPT easier and more efficient to use. Similar results have been reported in earlier technology-adoption studies (Han et al., 2024; Lai et al., 2023), where enjoyment enhances users' perception that a technology requires less effort to operate. Kılıç et al. (2025) further confirm that positive emotional experiences generated through ChatGPT's friendly feedback and alternative solution suggestions lead users to view the system as simple to navigate.

PEOU further demonstrated a strong positive effect on PU. The strong influence of PEOU indicates that when Gen Z PSTs find ChatGPT easy to use and comfortable, they are more likely to perceive ChatGPT as a practical and reliable tool that can enhance their teaching performance and instructional productivity, thereby driving their intention to adopt and use ChatGPT in

teaching practicum activities. This supports the results of Kılıç, et al. (2025), Zhang et al. (2026), and Sun et al. (2025), who highlight PEOU as a highly significant factor influencing GenAI acceptance among PSTs. Alejandro et al. (2024) further confirms that when PSTs perceive GenAI applications as easy to use and user-friendly, they are more likely to view these tools as useful for improving teaching methods and learning outcomes.

PEJ showed a statistically significant effect on ATT toward using ChatGPT-assisted teaching practicum, with a moderate effect size. This result aligns with previous studies that identified PEJ as a key determinant of favorable attitudes toward GenAI adoption (Adouani & Khenissi, 2024; Fitriati et al., 2025; Cano & Nunez, 2024). This result suggests that when Generation Z PSTs find the use of ChatGPT enjoyable, they are more likely to develop favorable attitudes toward its integration in their teaching practicum. The sense of enjoyment enhances their engagement and openness to experimenting with emerging technologies, reinforcing positive emotional responses. Therefore, intrinsic motivation, particularly enjoyment, should be viewed as a key factor in promoting technology acceptance in teacher education program.

The effect of PEJ on PU was significant but weak effect on PU in the ChatGPT-assisted teaching practicum, consistent with previous studies demonstrating that PEJ can indirectly enhance PU (Sabbir et al., 2020). However, the effect remained small because enjoyment influenced only the initial stage of use, whereas judgments of usefulness were shaped by practical and pedagogical considerations. PSTs perceived ChatGPT as useful only when its output was accurate, aligned with lesson objectives, and supported real teaching activities. Thus, although PEJ opened opportunities for users to recognize the value of the technology, stronger perceptions of usefulness were driven by task efficiency and alignment with professional teaching goals.

TR was found to have a significant but weak effect on ATT, indicating that TR contributes to shaping users' positive attitudes toward ChatGPT, yet its role remains secondary compared to other cognitive and experiential determinants. This finding aligns with previous studies (Albayati, 2024; Alzboon et al., 2025; Polyportis & Pahos, 2025), which emphasize that TR primarily serves to reduce uncertainty and foster initial comfort rather than directly shaping favorable evaluations. Among Indonesian Generation Z PSTs, this limited effect can be attributed to their advanced digital literacy and continuous engagement with AI technologies, which render trust an assumed condition rather than a key evaluative criterion. As digital natives, they tend to prioritize the system's performance, efficiency, and learning affordances over reliability concerns. Therefore, TR operates as a supportive enabler that facilitates acceptance but does not play a decisive role in shaping overall attitudes toward ChatGPT adoption.

TR was found to have a small but significant effect on PEOU of ChatGPT-assisted teaching practicum, consistent with previous studies (Al Shamsi et al., 2022; Alzboon et al., 2025; Octavia & Nugraha, 2024). However, the effect was relatively weak, indicating that TR plays only a minor role in shaping how easy ChatGPT is perceived to be. This may be due to the high digital confidence of Gen Z PSTs, who are comfortable using new technologies without heavily relying on TR. In practicum settings, they are more likely to focus on factors such as usefulness, enjoyment, and intuitive design when evaluating ChatGPT's support for lesson

planning and instructional tasks. Thus, while TR contributes to usability perceptions, it is not a primary driver of ChatGPT adoption for practicum-related teaching activities.

PU also showed a significant effect on ATT toward using ChatGPT-assisted teaching practicum, indicating that PSTs' ATT partially shaped by their perception of the tool's usefulness for lesson planning and content preparation. This result supports Alejandro et al. (2024), who found that teachers' positive attitudes toward AI applications are influenced by their perception of the technology's practical benefits in enhancing instructional effectiveness and learning outcomes. However, the effect was small because perceiving ChatGPT as useful alone does not strongly influence Generation Z PSTs' attitudes. Although they recognize that it can assist in preparing and organizing teaching materials, the need to review and edit outputs reduces its convenience and weakens its impact on attitude. This challenge is further amplified in Indonesia, where materials must strictly align with curriculum requirements and student characteristics, and differences in digital readiness across practicum schools limit reliance on the tool. Therefore, while ChatGPT is considered helpful, PU alone is insufficient to form a strong positive attitude toward its integration into the teaching practicum.

In contrast, PEOU demonstrated a negligible and non-significant influence on ATT toward ChatGPT adoption among Generation Z PSTs. This result differs from earlier studies, which reported that PEOU plays a major role in shaping users' attitudes toward new technologies (Alejandro et al., 2024; Falebita & Kok, 2024; Cano & Nunez, 2024; Geddam et al., 2024; Wu & Yu, 2024). However, Sun et al. (2025) support this finding, showing that PEOU does not significantly affect PSTs' ATT toward GenAI use. A plausible explanation is that Generation Z PSTs, having grown up using various digital platforms and possessing high digital fluency, do not view the simplicity of ChatGPT as an important factor that shapes their attitude toward using it. For them, ease of use is considered a basic requirement of any technology. Their evaluation instead focuses on the functional benefits of ChatGPT. As a result, PEOU does not influence their ATT because their attention shifts from how easy ChatGPT is to operate to the practical value it provides in their teaching tasks.

TR also showed no significant effect and contributed only a very small influence on the PU of ChatGPT among Generation Z PSTs. This result contradicts the findings of several previous studies (Al Shamsi et al., 2022; Alzboon et al., 2025; Octavia & Nugaraha, 2024). A possible explanation for this phenomenon is that Generation Z PSTs tend to distinguish between their general trust in technology and their evaluation of the academic benefits provided by ChatGPT. In the Indonesian context, where digital adoption varies across regions and educational institutions, Generation Z PSTs prioritize functional aspects, focusing on whether ChatGPT genuinely supports their academic or teaching-related tasks rather than considering how much they trust the technology. This supports Almogren et al. (2024), who found that TR does not always have a direct impact on PU.

Implications

The results offer several theoretical and practical implications. Theoretically, previous research on technology acceptance in education has largely emphasized cognitive determinants, as conceptualized in TAM (Davis, 1989; Venkatesh & Davis, 2000). This study extends TAM by incorporating PEJ and TR as affective and relational dimensions to explain Generation Z PSTs acceptance of ChatGPT-assisted teaching practicum. The significant influence of PEJ on PU, PEOU, and ATT demonstrates that emotional engagement and intrinsic motivation are central predictors of technology acceptance in ChatGPT-supported teacher education. The results indicate that enjoyment operates not merely as an emotional response but as a motivational force that enhances users' perceptions of value and usability. By positioning enjoyment as a critical determinant of user perception, this study expands the theoretical understanding of TAM to capture affective experiences in technology adoption, particularly within ChatGPT contexts.

Second, while prior studies have shown that TR significantly influences PU in various digital environments (Al Shamsi et al., 2022; Alzboon et al., 2025; Octavia & Nugraha, 2024), the current study reveals that TR does not directly affect PU among Generation Z PSTs. This result refines the TAM extension by indicating that digital-native users may separate relational trust from perceived utility, focusing instead on pragmatic factors such as task relevance and performance support. However, the positive yet weak influence of TR on PEOU and ATT highlights its indirect role in shaping usability perception and emotional acceptance. This nuanced understanding contributes to advancing TAM by contextualizing trust as a secondary, context-sensitive construct that varies across user generations and technological familiarity levels. Third, the non-significant relationship between PEOU and ATT challenges the traditional TAM assumption that PEOU consistently predicts ATT (Aguilos & Fuchs, 2024; Geddam et al., 2024). For Generation Z PSTs, ease of use has become an expected baseline rather than a differentiating factor, reflecting their high digital fluency and constant interaction with intuitive interfaces. This result implies that affective and experiential constructs, such as enjoyment and curiosity, play stronger roles in attitude formation than usability alone. Consequently, this study contributes to the evolution of TAM by suggesting the inclusion of digital maturity and affective familiarity as moderating factors influencing user attitude. Finally, the strong relationship between attitude and intention to use ChatGPT confirms the central mediating role of attitude in converting perceptions into intention to use ChatGPT. Positive emotional experiences thus emerge as the most influential predictors of sustained technology use. These insights contribute to an affective–relational extension of TAM, integrating PEJ and TR as essential components for understanding ChatGPT acceptance-assisted teaching practicum in teacher education.

Practically, the results have important implications for teacher education, curriculum design, and institutional practice. In the context of teacher education, the results highlight the importance of fostering affective engagement to develop PSTs' readiness to adopt ChatGPT. Training programs should include interactive and hands-on activities, such as using ChatGPT for lesson planning, instructional material design, or classroom management simulations, to make learning experiences both enjoyable and meaningful. These practices can enhance curiosity, confidence, and creativity while reducing cognitive load and anxiety during practicum activities.

Incorporating reflective discussions or peer-sharing sessions on ChatGPT use can further deepen emotional connection and critical awareness, encouraging sustained and ethical adoption of ChatGPT in teaching.

From a curriculum perspective, the findings indicate the need to embed AI literacy and ethical competence into teacher education programs. Since TR contributes to positive attitudes, curricula should include modules on data privacy, bias awareness, information reliability, and responsible AI use to build both digital confidence and ethical sensitivity. Additionally, the significant relationship between PEOU and PU emphasizes the importance of usability-focused digital competencies, such as prompt formulation, contextual adaptation, and critical evaluation of AI-generated outputs. Embedding these skills within the curriculum ensures that PSTs can integrate ChatGPT not only technically but also pedagogically and ethically in real classroom contexts.

At the institutional level, the results underscore the need for supportive policies, infrastructure, and professional development to sustain ChatGPT adoption. Institutions should implement transparent AI policies that address data protection, academic integrity, and ethical compliance to strengthen users' trust and confidence. Regular professional development programs and ongoing technical support can further encourage responsible and confident use of ChatGPT in teacher education. Collaborations between universities and technology developers can also facilitate the creation of localized AI training platforms and user-friendly interfaces tailored to the needs of PSTs, ensuring accessibility, relevance, and long-term engagement.

Conclusion

This study examines the determinants influencing Generation Z PSTs' acceptance of ChatGPT-assisted teaching practicum by extending the original TAM with two additional constructs: PEJ and TR. The results revealed that PEJ and TR significantly shape PEOU and ATT with PEJ having the strongest impact. ATT was also found to be the strongest predictor of IUC, emphasizing that emotional engagement, trust, and confidence are essential in encouraging technology adoption. The proposed framework advances TAM by integrating affective and relational dimensions that explain how intrinsic motivation, confidence, and perceived reliability contribute to technology acceptance in teacher education. Beyond theoretical contributions, these results provide practical guidance for educators and policymakers to develop practicum experiences that encourage exploration, build trust in ChatGPT, and strengthen digital competencies, ensuring the effective and sustainable use of ChatGPT in future instructional practices. This study not only advances theoretical understanding of ChatGPT acceptance in teacher education but also underscores the practical imperative of preparing future educators to confidently and ethically integrate ChatGPT into evolving digital learning environments.

Limitation and Future Research

This study acknowledges some limitations, which can be categorized into methodological, theoretical, and contextual categories. Methodologically, the use of convenience sampling may have introduced sampling bias and limited the generalizability of the findings. Future research

should consider employing probabilistic or stratified sampling techniques to ensure a more representative sample. Moreover, the study exclusively employed Likert-scale self-report instruments, which may not fully represent authentic user behavior and are susceptible to social desirability bias. To strengthen the validity and depth of future findings, researchers are encouraged to use mixed-method designs that combine surveys with qualitative techniques such as interviews, classroom observations, or behavioral analytics. Additionally, the cross-sectional design limits the ability to observe changes in PSTs' acceptance of ChatGPT over time. Longitudinal research would allow scholars to track evolving attitudes, confidence, and usage behavior, offering deeper insights into how continuous interaction with ChatGPT influences sustained adoption. Theoretically, this study examined only two psychological constructs, PEJ and TR, which provide a relatively narrow understanding of the broader motivational and contextual factors influencing technology acceptance. Future research should expand the framework by incorporating additional variables such as self-efficacy, prior technology experience, mentor support, institutional resources, and classroom conditions. Examining these factors together would offer a more comprehensive understanding of the mechanisms shaping the adoption and continued use of ChatGPT in teacher education contexts. Contextually, the study involved PSTs from Central Java, Indonesia, which may limit the transferability of the results to other regions or cultural contexts. Future research should include participants from diverse geographical and institutional settings and conduct cross-cultural comparisons to explore how contextual and cultural factors shape the integration of ChatGPT in teacher education.

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Disclosure Statement

The authors declare no conflict of interest related in this study.

Ethical Statement

The Ethics Committee of Universitas Muhammadiyah Surakarta approved this study. Participants were informed about the research purpose, procedures, and their rights, particularly the right to withdraw without penalty. Only participants who provided consent were permitted to proceed with the survey. Data were collected anonymously, and strict confidentiality protocols were followed to ensure participant privacy and data protection throughout the research process.

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Appendix A

Constructs and Questionnaire Items Related to ChatGPT Acceptance and Use

Construct	Number of Items	Items Codes	Sample Items
PEJ	3	PEJ1	I enjoy using ChatGPT to support my lesson planning and teaching activities.
		PEJ2	I find using ChatGPT in preparing teaching materials enjoyable and engaging.
		PEJ3	Working with ChatGPT during my teaching practicum is a fun and motivating experience.
TR	5	TR1	I believe using ChatGPT in my teaching practicum is secure.
		TR2	I believe that the information exchanged through ChatGPT during lesson preparation is secure.
		TR3	I trust that my personal and professional data will be kept private when interacting with ChatGPT.
		TR4	I have confidence in ChatGPT's security features and its ability to protect my information.
		TR5	I believe that ChatGPT adequately protects user's privacy.
PU	4	PU1	Using ChatGPT helps me design and deliver lessons more effectively during my practicum.
		PU2	ChatGPT enhances the quality of my lesson preparation and teaching performance.
		PU3	Using ChatGPT makes it easier to access relevant teaching materials and ideas.
		PU4	Using ChatGPT increases my productivity in planning and conducting lessons.

PEOU	3	PEOU1	It is easy for me to use ChatGPT to make teaching preparation for my practicum.
		PEOU2	Preparing lessons with ChatGPT is simple and understandable.
		PEOU3	I feel capable of becoming competent in using ChatGPT as part of my teaching practicum activities.
ATT	4	ATT1	Using ChatGPT to assist my teaching practicum would be a favorable and beneficial choice.
		ATT2	Using ChatGPT is better than using other digital tolls for lesson planning.
		ATT3	I enjoy using ChatGPT for teaching and lesson preparation.
		ATT4	It is beneficial to use ChatGPT compared to other educational applications.
IUC	3	IUC1	I intend to use ChatGPT to support my teaching practicum.
		IUC2	I believe using ChatGPT will continue in my teaching practice.
		IUC3	I plan to keep using ChatGPT for teaching-related tasks in the next six month.

Effects of a Project Management MOOC on Employability Skills and Career Self-Perception: Comparing Academic Cohorts and Free Auditors in a Pre-test/Post-test Design

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Abstract
This study examines the impact of a Project Management MOOC on self-perceived employability and career self-perception, comparing academic cohorts (AC) who enroll as part of formal education with free auditors (FA) who participate voluntarily. Drawing on a competence-based approach, we assess skill-based employability through dimensions of occupational expertise, anticipation and optimization, and personal flexibility, and evaluate career self-perception via measures of external marketability, career ambition, and motivation. Prior research tends to show that the active population puts importance on skills and social networks, whereas students view MOOC micro-credentials as a means to access the labor market. However, a research gap remains regarding how different learner groups leverage MOOCs for professional development. Data was collected during the course via two surveys administered at pretest (N = 3,059) and posttest (N = 1,357), with paired analyses on 1,301 participants. Results indicate that FA exhibit significantly higher scores in skill-based employability and career motivation at both pre- and post-test, whereas AC demonstrate better scores in external marketability and career ambition, with no significant differences observed in personal flexibility for both groups. These findings highlight that the subdimensions of employability, whether approached from a skill-based or dispositional perspective, do not behave homogeneously but vary depending on contextual factors such as learner group and course subject matter. The study contributes to the integrative employability research agenda and underscores the importance of contextualizing MOOC effects according to learner status. These results highlight the need for further investigation about the mechanisms through which MOOCs enhance practical competencies and influence career self-conception across diverse learner populations, paving the way for future research to better understand how distance learning settings can better foster employability.

Keywords: Academic cohorts, graduate students, MOOC, employability, skills, disposition

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MOOCs attract a diverse range of learners: On the one hand, many students are required to enroll in MOOCs as part of their formal university curriculum, integrating these courses into their mandatory academic programs (Watted & Barak, 2018). On the other hand, a large population of active individuals enroll voluntarily in lifelong learning and professional development dynamics (Milligan & Littlejohn, 2017). These learners, often professionals seeking to enhance their skills or explore new fields, are motivated by the flexibility and accessibility that MOOCs offer, allowing them to balance education with other personal and professional responsibilities (Chaker et al., 2022). If this dual enrollment pattern highlights some democratic aspect of MOOCs, it also underscores the need to understand the distinct motivations and outcomes associated with each learner group. For instance, while students sometimes view MOOCs as a pathway to enhancing their employability (Santandreu Calonge & Shah, 2016), potential recruiters see them as a means of professional development (Walton Radford et al., 2014).

Specifically, there is a research gap concerning the extent to which these two learner groups differ in their employability outcomes and career self-perceptions within the MOOC context. This article studies the effects of a project management MOOC on participants' self-perceived employability and career self-perception. We employ a person-centered (Monteiro et al., 2022), psychological approach to study employability (Vanhercke et al., 2014), a competence-based approach (Van Der Hayden & Hayden, 2006) to evaluate self-perceived employability, and a dispositional approach of employability (Fugate, Kinicki & Ashforth, 2004) to evaluate career self-perception. The latter refers to "the perceptions regarding one's added value at the (internal or external) labor market" (De Vos et al., 2011), as well as, I might add, the perceptions of one's congruence with the demands of the current labor market. This article aims to answer the following main research questions:

> Are there any differences in terms of self-perceived employability between university students and the general population freely enrolled in a MOOC before and after the end of the course? Are those potential differences observed across different employability approaches?

These research questions seek to better understand how dispositional and competence-based approaches result in measurable differences in self-perceived employability and career self-conception after a MOOC. In doing so, this study aims to contribute to three key scientific objectives: 1) the need to better understand differential outcomes for online and distance learning programs, in terms of job- and career-related and professional development outcomes; 2) the need to conduct integrative employability research (Forrier et al., 2015; Römgens et al., 2020); and 3) to bridge the gap about the "limited theoretical or practical exchange" between graduate employability and career development (Healy et al., 2022, p. 799).

MOOCs and Employability

MOOCs in Higher Education: Between Compulsory Programs and Professional Development Dynamics

MOOCs as Drivers and Replacements in Higher Educational Settings

MOOCs (Massive Online Open Courses) were accompanied since their conception by the promises that they will generalize global access to higher education pedagogical contents (Reich, 2020). The idea was indeed to provide students from around the world educational content provided by the best (Western) universities. This would allow different populations to benefit at a reduced cost from course units offered by "prestigious" universities, as well as

people who are employed, who could take advantage of the flexibility of the MOOC format (Alcorn et al., 2015). Rather than transforming the higher educational system, MOOCs were integrated into existing university programs (Reich & Ruipérez-Valiente, 2019).

Building on these premises, MOOCs are progressively integrated into traditional higher education systems, providing an effective means to supplement on-campus instruction with scalable, flexible, and accessible distance learning elements within undergraduate and graduate programs (Griffiths et al., 2015). This integration allows institutions to diversify their educational offerings by embedding digital course components that complement conventional curricula (Bralić & Divjak, 2018; de Lima Guedes et al., 2022). Moreover, some institutions have begun to mandate MOOCs as part of their academic programs, in part to ensure that all students acquire critical digital literacy and lifelong learning skills essential for the modern workforce (Israel, 2015), but also because MOOCs fit well into a busy student and academic program time schedules (Shapiro et al., 2017; Li et al., 2022). This blended approach has been shown to enhance learning outcome (De Moura et al., 2021). It also aligns educational practices with the rapidly evolving demands of higher education in a digital era. For Williams (2024), enrolled higher education students "access MOOCs as learning and teaching resources as part of existing courses, using video lectures, reading lists, and other open educational resources" (p. 2).

Integrated MOOCs and micro-credential programs in universities' curricula can be seen as a means of better preparing students for the evolving demands of the labor market. These innovative educational approaches not only supplement traditional academic offerings but also equip graduates with supposedly practical, industry-recognized skills that enhance their overall employability (Dillahunt et al., 2016; Rothwell et al., 2008). Indeed, the development of students' employability "is most effective through a processual approach in which the responsibility for employability development is shared by institution, industry and student" (Bennett, 2018, p. 50). This could take the form of micro-credentials and for-credit activities (Burke et al., 2017; Jackson et al., 2024), or any program that recognises students' need to develop in advance "a set of person-centred constructs that involve individual proactivity and reflexivity relating to career identity, personal adaptability, and social and human capital" (Bennett et al., 2017; Fugate et al., 2004, as cited in Bennett, 2018, p. 50). In other words, it is the responsibility of higher education institutions to support students in cultivating their dispositional development with respect to these dimensions. However, despite their potential, the efficacy of such programs into university curricula to enhance graduates' readiness for the labor market remains uncertain. Further research is needed to determine whether these innovations translate into tangible improvements in employability outcomes. Indeed, the low level of graduates' transferable skills is regularly reported by employers, in part due to "the low connectivity between the studied subject and the subsequent occupation" (Behle, 2020, p. 113). Hence, focusing on the development of self-perceived employability, rather than on immediately transferable skills, can help us understand to what extent a program participated in building employability capacity among higher education students (Bennett, 2018; Jackson et al., 2024).

MOOCs in the Context of Professional Development and Lifelong Learning

With the rapid diffusion of digital technologies and the widespread availability of online resources and networks, new forms of learning have become possible, and MOOCs have emerged in this context as a timely (Barker et al., 2024) key response, offering scalable and flexible formats for ongoing professional development (Torcivia Prusko, 2020). They have become a popular tool for professional development across various industries (Chaker & Bachelet, 2020) for "vocational learners" (Williams, 2024). A large-scale survey of MOOC

completers found that around half of the respondents took the course primarily for career-related reasons (Zhenghao et al., 2015). Among them, 87% reported that the MOOC benefited their professional development, improved skills for their current job (62%), aided them in finding a new job (26%), or provided them support for launching their own business (9%). Indeed, MOOCs are being utilized more frequently not only to enhance current occupational skills but also to specialize further in one's field through the acquisition of new skills (Milligan & Littlejohn, 2014). In their inductive research, Watted and Barak (2018) found that general MOOC completers (*vs*. "university-affiliated" completers), declared pursuing career benefits across four subdimensions: "professional competence, product development, research relevance, and career change" (p. 14).

For instance, MOOCs may contribute to career advancement not just by fostering skill development, but also by offering micro-credentials from educational institutions (Novella et al., 2024). MOOCs aimed at enhancing professional competencies attract a diverse range of learners with varying educational backgrounds (Milligan et al., 2013). However, continuous professional education presents several challenges, including the need for professionals to independently manage their online learning and the imperative to emphasize the integration of theoretical knowledge with practical skills in professional contexts (Milligan & Littlejohn, 2014; Mori & Ractliffe, 2016; Chaker & Bachelet, 2020; Chaker et al., 2022).

The inherent characteristics of MOOCs—their openness and online accessibility—make them particularly well-suited for workplace learning. This format can facilitate the transfer of skills between professional practice and learning environments, allowing learners to immediately apply new knowledge in their work contexts (Milligan & Littlejohn, 2014; Egloffstein & Ifenthaler, 2017). Furthermore, the flexibility of MOOCs enables professionals to engage in continuous learning without significant disruption to their work schedules, making them an attractive option for both employers and employees seeking to enhance their skills and knowledge base (Bachelet & Chaker, 2017; Castañeda et al., 2018). In their research, Chaker et al. (2022) demonstrated that MOOC performance among free-auditors—primarily active individuals such as managers and job seekers—was largely contingent upon the time they could allocate to course activities.

However, while MOOCs can enhance skill-based employability, they may not offer greater employability benefits to those who have never been able to attend school or had a formal job (Callonge & Shah, 2016; Kizilcec et al., 2017). Therefore, MOOCs should be seen as a complement to formal education and work experience, rather than a replacement (Mohsen, 2016). This perspective aligns with the idea that MOOCs can serve as a strategic resource for professional development within and outside institutions, particularly in higher education settings (Despujol et al., 2022). While MOOCs offer flexibility and accessibility, they are most effective when integrated into a broader educational or professional development strategy. In this context, professional development serves as a catalyst for employability by enabling individuals to align their skills with the demands of the Internet and external job market (Bates et al., 2019; Shiri et al., 2023). In this perspective, university students are also concerned by the need to foster and demonstrate their employability skills (Choate et al., 2016; Cleary et al., 2019).

The Plurality of Employability Approaches

Despite its importance, there is no clear consensus on the exact definition or dimensions of employability. The nature and structure of work have experienced dramatic changes, resulting in an environment where job security has become increasingly uncertain in the broader context of the transition from an industrial to a postindustrial society (Thijssen &

Van der Heijden, 2003). This shift represents a transition from traditional organizational career paths to "boundaryless careers" and "protean careers" (Mirvis & Hall, 1994; Hall & Mirvis, 1995). These modern career models prioritize individual control over organizational control. A protean career involves a variety of personal experiences, including education, learning, working across different organizations, and changing professional fields. Success in these careers can be internally defined, focusing on psychological satisfaction rather than external achievements. Specifically, understanding the evolving career landscape hinges on the concept of employability. In this context, employability has gained prominence as a key factor in addressing labor market imbalances, shaping educational policies, managing employment relationships, and understanding individual job-seeking strategies. Its implications are extensive, affecting political, social, economic, and managerial spheres. In human resource management, employability is increasingly viewed as a mutual responsibility between employers and employees (Forrier, De Cuyper & Akkermans, 2018).

Competence-Based Approach of Employability

Employability generally refers to an individual's ability to obtain and retain employment: Rothwell and Arnold (2007) define employability as "the ability to keep the job one has or to get the job one desires" (p. 25). For instance, this can involve a variety of competencies, skills, and attributes that make a person more attractive in the labor market, including technical skills, soft skills, adaptability, and commitment to continuous learning. The emphasis on employability highlights a shift from job security to career security, where individuals are responsible for maintaining their employability through ongoing learning and skill development (Guilbert et al., 2016). This competence-based approach to employability focuses on the individual competences, in terms of know-how and knowledge, a person possesses (Van der Heijden et al., 2009). For van der Heijde and van der Heijden (2006), "besides adaptive behavior, employability may contain personal elements such as personality, attitudes, motivation, and ability," but also: "employability represents the combination of specific and more generic competence," (p. 453), or as the authors put it, "a more broader competence package" (p. 453), such as corporate sense, anticipation, and optimization, personal flexibility, and balance. The competence-based approach relies on the idea that employability can be enhanced by developing specific skills and knowledge that are valued in the job market. This approach suggests that hiring and employee development should be based on their skill sets instead of their work history (Gabor, Blaga & Matis, 2019). It also encourages continuous learning and skill development to keep up with the changing job market.

Dispositional Approach of Employability

The dispositional approach to employability, on the other hand, emphasizes attitudes, personality, and individual dispositions, in terms of career management and focus. The dispositional approach to employability is defined as a constellation of individual differences that predispose individuals to proactive adaptability specific to work and careers (Fugate & Kinicki, 2008). It postulates that employability depends not only on technical skills but also on a person's attitudes and behaviors, and considers personal traits and characteristics, such as motivation, resilience, and adaptability, in the comprehension of an individual's career dynamics. Dispositional employability can then be understood as a psychosocial process that facilitates the enactment of behaviors directed toward career self-management (Brown et al., 2024). For example, a study on dispositional employability and self-regulation in antisocial and prosocial personalities found that career motivation explained 6.4% of the variance in dispositional employability (Lisá & Valachová, 2023). This suggests that career motivation is a significant factor in an individual's employability from a dispositional perspective. Career motivation, which can be understood as the drive or desire to achieve success and progress in

one's professional life, influences how individuals adapt to their work and career circumstances.

Career ambition can also be considered as part of the dispositional approach to employability. It reflects an individual's drive and motivation to achieve career-related goals and can be seen as a dispositional trait that influences one's adaptability in the workplace (Garavan et al., 2021). It can affect how an individual approaches career development, job changes, and other work-related challenges.

External Dimension of Employability

Both skill-based and dispositional approaches put importance on individual characteristics in terms of employability (Forrier et al., 2018). However, "employability is not only about individual attributes. (…) There are also external factors including the state of the contemporary external labour market" (Rothwell & Arnold, 2007, p. 25). External marketability refers to an individual's perceived attractiveness to external organizations (Park et al., 2022). It is related to how individuals perceive their own skills, experiences, and qualifications that are valued in the external labor market. Self-perceived employability was found in previous research as a positive predictor of perceived marketability (De Vos et al., 2011). Hence, marketability is a belief in one's value to current and future employers (Eby et al., 2003), a construct that appears to be more closely linked with dispositional employability than with purely skill-based factors. Indeed, the way individuals appraise their marketability tends to be filtered through their internal dispositions and self-beliefs (Berntson et al., 2008; Lisá & Valachová, 2023). Therefore, perceived marketability can be seen as a function of dispositional factors, highlighting the role of subjective self-assessment in shaping career prospects (Bargsted, 2017). However, Rothwell and Arnold (2007) also posited that external perceived marketability "relates to individuals' self-perception of their worth (based more on their personal skills than features of their occupation) in the external labour market" (p. 27). Thus, perceived marketability can be seen as an interplay between the objective possession of personal skills and the subjective, dispositional evaluation of these skills. In both approaches, external marketability can although be linked to a relational perspective of employability (Forrier et al., 2018); individual attributes must be aligned with market's needs and realities in order for them to be reified into real employability outcomes.

Thus, it can be argued that external marketability occupies a hybrid position between dispositional and skill-based constructs. On the one hand, it is dispositional in that it involves an individual's subjective assessment of their own qualities and the beliefs they hold about their capabilities. On the other hand, it also reflects a skill-based dimension, as it considers how well these personal attributes align with the demands of the labor market. In fact, perceived external marketability serves as a means of evaluating the congruence or alignment between an individual's characteristics and the external employment environment, as self-assessed by the individual, in a relational and situated perspective. Consequently, some research focuses on determining whether external marketability functions more as a reflection of intrinsic, dispositional factors or as an outcome of acquired skills (Fugate et al., 2004; Rothwell & Arnold, 2007).

What Are the Employability Outcomes for Academic Cohorts and Free Audits in a MOOC?

This research overview highlights possible differences between academic cohorts (AC), who are required to take MOOCs as part of their academic program, and free auditors (FA), who enroll voluntarily. These groups somehow appear to hold distinct perceptions and use different strategies to leverage MOOCs for enhancing their employability.

> AC, who enroll in MOOCs as part of their formal education, typically benefit from institutional validation and complementary certifications that bolster their self-perceived employability and career self-conception (Rothwell, Herbet & Rothwell, 2008; Rothwell, Jewel & Hardie, 2009). In contrast, FA, often working professionals or job seekers, must adopt a self-directed, skills-based approach, emphasizing cross-competences and continuous adaptation to labor market demands (Van der Heijden et al., 2009; Forrier et al., 2015; Forrier et al., 2018). These differences raise research questions regarding the extent to which these two learner groups differ in their employability outcomes and career self-perceptions, specifically when taking MOOC. The research questions are as follows: RQ1: To what extent are there between-groups significant differences (AC vs. FA) in terms of competence-based employability and career self-conception at pretest?
>
> RQ2: To what extent are there between-groups significant differences (AC vs. FA) in terms of competence-based employability and career self-conception at posttest?
>
> RQ3: To what extent are there within-subjects significant differences (competence-based employability vs. career self-perception) between pre- and post-test?
>
> RQ4: To what extent are there within-subjects significant differences (competence-based employability vs. career self-perception) depending on group membership (AC vs. FA) between pre- and post-test?

Methods

Context of the Study

The Project Management (PM) MOOC (https://mooc.gestiondeprojet.pm) is a biannual MOOC in project management delivered by Centrale Lille (France). It aims to certify already employed individuals through flexible online courses that provide timely professional development (Barker et al., 2024) and also targets higher education students as part of their for-credit programs (Lee et al., 2022). Launched in 2013, it is widely recognized as one of the first certifying French MOOCs and has been offered twice a year ever since, with well over one hundred thousand enrolments across successive sessions (Verzat, 2020). The course is fully online, open to the general public, and delivered in French, with an estimated workload ranging from roughly 20 to 50 hours. It combines short video lectures, quizzes, discussion forums, live Q&A sessions and shared note-taking, organized over a four-week structure with a common "core" track. Each week aims the acquisition of specific skills and knowledge about PM: Week 1 is about project management fundamentals; Week 2 is about the essential tools to get a project started; Week 3 is about advanced tools in PM, and Week 4 is about risks management. Learners can follow a free audit track or complete graded activities and a proctored final exam to obtain a certificate that is recognized for ECTS credits at Centrale Lille, making the MOOC relevant both for initial higher education and for continuing professional development (Chaker, 2017). Hence, a substantial proportion of

participants are already in employment and report using the MOOC to update or formalize project-management skills that are directly transferable to their workplace, which makes it a particularly relevant context for studying online professional development and employability outcomes. Enrolled students constitute so-called academic cohorts (AC) of graduate students: The MOOC is part their master's program, as a mandatory course. These students from partners institutions are enrolled through their professors. AC students come from French higher education institutions (universities and high-rated *Grandes Ecoles*); they were therefore treated as students whose primary status is education and not as members of the active labor force, even if some of them may have held part-time or occasional jobs alongside their studies. In terms of model, those institutions often integrate the PM MOOC in their respective programs as a replacement of a traditional course about project management, with a direct alignment of the MOOC content with the existing courses in the curriculum (Pérez-Sanagustín et al., 2017). By contrast, the free auditors (FA) group is composed of self-enrolled participants, the large majority of whom are already active in the labor market. The present study uses the data gathered in the context of PM MOOC's 19th edition (2022), for which 9,445 participants enrolled, of whom 6,705 validated the core track.

Sample and Procedure

Two research surveys (RS) were inserted into the course: RS1 (pre-test) was integrated in week 0 of the course (before the official launch of week 1) and RS2 (post-test) was integrated in the course's week 4. Answering the surveys was non-mandatory and complete anonymity was assured. The sample is N = 3,059 at pre-test (41.60% females, mean age = 29.74) and N = 1,357 at post-test (41.90% females, mean age = 28.29). After data alignment using the participants' anonymous course IDs (automatically provided using enrolments tokens), the paired sample (that will be used for pair-wised comparisons between pre- and post-test) involves in total N = 1,301. The AC group was identified in the dataset using the "academic institution" field that is automatically generated in the MOOC platform data export, allowing us to sort out learners enrolled via a higher education institution. The number of participants in the surveys recorded a 44% attrition between both RS, as shown in Table 1:

Table 1

Study Samples Across Tests

N	Academic cohorts	Free audit participants	Total
Pre-test	1,770	1,289	3,059
Post-test	867	490	1,357
Aligned data	858	443	1,301

Among FA, the sample consisted of business owners (2.10%), individuals in higher managerial and professional occupations (47.40%), employees (11.70%), intermediate professionals (9.80%), jobseekers (23.20%), and non-active individuals (1.80%).

Measures

To answer our research questions, we used and adapted already existing questionnaires about employability, in such a way that the items of the subscales suit already employed persons but also higher education students. Hence, we selected items from previously validated scales or subscales, when applicable to both students and active population (see Appendix for the list of items). We only selected items from unifactorial scales or subscales, to ensure satisfactory internal consistencies.

Skill-Oriented Employability: Competence-Based and Multi-Dimensional Measurement of Employability

Van der Heijde and Van der Heijden (2006) and Van der Heijden et al. (2009) focus on employability as a skill-based concept. They define employability as "the continuous fulfilling, acquiring or creating of work through the optimal use of competences" (Van der Heijden et al. 2009, p. 453). From Van der Heijden et al. (2018) domain-independent instrument measuring self-perceived employability, we adapted the five items of the Occupational Expertise (OE) dimension (e.g., How would you rate the quality of your skills overall?), the four items from the Anticipation and Optimization (OA) dimension (e.g., I consciously devote attention to applying my newly acquired knowledge and skills), and three items from the Personal Flexibility (PF) dimension (e.g., How quickly do you generally anticipate and take advantage of changes in your environment?). Since the last two dimensions (Corporate Sense and Work/Life Balance) are too work-specific, we did not use them in our research.

Career Self-Perception: Perceived External Marketability

Regarding external employability, as measured by external marketability, Rothwell and Arnold (2007) contend that self-perceived employability "relates to individuals' self-perception of their worth (based more on their personal skills than features of their occupation) in the external labour market." This perspective highlights that while personal skills are indeed a component of skill-based employability, the emphasis on self-assessment underscores a significant dispositional element, especially when individuals (such as graduate students) possess only partial knowledge about the state of the job market. In other words, the valuation of one's personal skills is inherently subjective, influenced by internal factors such as self-efficacy, confidence, and adaptability (Fugate, Kinicki, & Ashforth, 2004). Thus, perceived marketability can be seen as an interplay between the objective possession of personal skills and the subjective, dispositional evaluation of these skills, which, in our case, were dominating among graduate students. We adapted five items from the questionnaire of Rothwell and Arnold (2007) and Rothwell et al. (2009) in relation to the perceived external marketability (EM). For Eby et al. (2003), perceived EM corresponds to "the belief that one is valuable to other employers" (p. 690). Employability thus includes a "personal-organizational" dimension. An example of item: *Professionals in the area you are aiming for are in high demand in the labor market* (Rothwell & Arnold, 2007; Rothwell et al., 2009).

Career Self-Perception: Career Ambition

An internal–external split of employability is structured around a distinction between perceptions of the external labor market and individual self-belief, respectively (Rothwell, Herbert & Rothwell 2008). Internal employability is believed to relate to the perception of "(internal) attributes, skills, abilities, engagement with study, and ambition" (Rothwell, Herbert & Rothwell, 2008, p. 6). For Rothwell and colleagues (2009), the career ambition six-item scale we used in the present study is a "proxy for perceptions of future career success" (Rothwell, Jewell & Hardie, 2009, p. 155), and can be used for both students and general populations.

Career Self-Perception: Career Motivation

In terms of career self-perception, we also aimed to measure to what extent participants project themselves in terms of career planification. We used four items from the *career insight* subscale in Noe, Noe, and Bachhuber's *Career motivation* questionnaire (1990) (e.g., *To what extent do you have a specific career goal?*). Career motivation (CM) is an essential drive of employability, as it relates to individual agency towards career-related goals, and is among the dimensions that compose dispositional employability (Fugate & Kinicki, 2008). It can contribute to employability, as motivated graduates are more likely to actively seek and capitalize on opportunities (Brown et al., 2021).

Ethical Considerations

This study was conducted in accordance with Centrale Lille's institutional guidelines for pedagogical research and with the General Data Protection Regulation (GDPR). In line with these guidelines, formal approval from a research ethics committee was not required for anonymous, voluntary questionnaires administered in the context of routine teaching activities. Participation in the survey was entirely voluntary, no incentives were offered, and no identifiable or sensitive personal data were collected. At the beginning of each questionnaire, participants were informed that their responses would remain anonymous and would be used solely for the purposes of this study.

Results

Descriptive Results

The intercorrelations table yield significant ($p < .001$) relationships between all constructs at pre-test and at post-test. There is an exception for career motivation: There is no correlation with external marketability at pre-test, and the relationship is rather weak at post-test ($r = .036$; $p > .05$ and $r = .070$; $p < 0.05$; respectively). Hence, there is a rather weak or non-existent link between a relational aspect of employability and career insight as a personal trait or internal attribute.

Table 2

Correlation Table Between Constructs at Pre-test (Post-test Between Brackets)

	OE	A&O	PF	CA	EM
A&O	.370** (.420**)				
PF	.366** (.327**)	.431** (.457**)			
CA	.208** (.241**)	.353** (.408**)	.245** (.290**)		
EM	.170** (.186**)	.253** (.298**)	.210** (.228**)	.253** (.279**)	
CM	.193** (.224**)	.310** (.359**)	.173** (.273**)	.236** (.336**)	0.036 (.070*)

Between-Groups Differences: Free Auditors Display Higher Skill-Based Employability and Career Motivation, While Academic Cohorts Display Higher Career Self-Perception

Between-Groups Differences at Pre-test

All constructs at pre-test display satisfying to excellent internal consistencies ($.69 < \alpha < .85$). Results show at pre-test (Table 3) that free audit participants (FA) declare significantly higher skill-based employability than academic cohorts (AC). They score higher occupational expertise (OE) (M = 3.66; SD = .60 and M = 3.46; SD = .61; $t = -8.90$; $p < .001$, respectively), and higher anticipation and organization (A&O) (M = 3.70; SD = .72 and M = 3.64; SD = .64; $t = -2.26$; $p = .024$, respectively). Differences are not significant for personal flexibility (PF). FA also declare higher career motivation (CM): M = 3.45; SD = .89 and M = 3.33; SD = .87 ($t = -3.78$; $p < .001$), respectively.

Conversely, AC declare higher career-related perceptions than FA. They score higher external marketability (EM) (M = 3.57; SD = .73 and M = 3.01; SD = .82; $t = 19.67$; $p < .001$, respectively), and higher career ambition (CA) (M = 3.47; SD = 1.13 and M = 3.33; SD = .87; $t = 12.81$; $p < .001$, respectively).

Table 3

Employability and Career Self-Perception Scores at Pre-test by Group

	Academic cohorts		Free Auditors				Total		
	M	SD	M	SD	t	p	M	SD	α
Occupational Expertise	3.45	.61	3.70	.60	-8.90	.001	3.54	.60	.79
Anticipation & Organization	3.64	.65	3.70	.72	-2.26	.024	3.67	.68	.74
Personal Flexibility	2.98	.91	3.99	.93	-1.25	.211	3.01	.93	.82
External Marketability	3.56	.73	3.01	.82	19.67	.001	3.33	.82	.80
Career Ambition	3.47	1.13	2.93	1.20	12.81	.001	3.25	1.18	.85
Career Motivation	3.33	.87	3.45	.89	-3.78	.001	3.38	.88	.69

Between-Groups Differences at Post-test

All constructs at post-test display acceptable to excellent internal consistencies ($.70 < \alpha < .82$). The same tendencies than at pre-test were observed (Table 4): between-groups differences are constant in terms of competence-based approach of employability and career self-perception.

Table 4

Employability and Career Self-Perception Scores at Post-test by Group

	Academic cohorts		Free Auditors				Total		
	M	SD	M	SD	t	p	M	SD	α
Occupational Expertise	3.44	.63	3.83	.56	-11.45	.001	3.57	.63	.78
Anticipation & Organization	3.71	.64	3.83	.64	-3.44	.001	3.75	.64	.72
Personal Flexibility	3.12	.85	3.18	.89	-1.69	.102	3.14	.86	.80
External Marketability	3.53	.74	3.04	.83	10.42	.001	3.56	.81	.82
Career Ambition	3.41	1.15	3.01	1.20	5.17	.001	3.27	1.18	.82
Career Motivation	3.30	.86	3.56	.83	-5.44	.001	3.39	.86	.70

For both pre- and post-test, FA yield significantly higher score than AC for skill-based employability (OE and A&O) and career motivation. Conversely, AC yield significantly higher scores than FA for career self-perception (external marketability and career ambition).

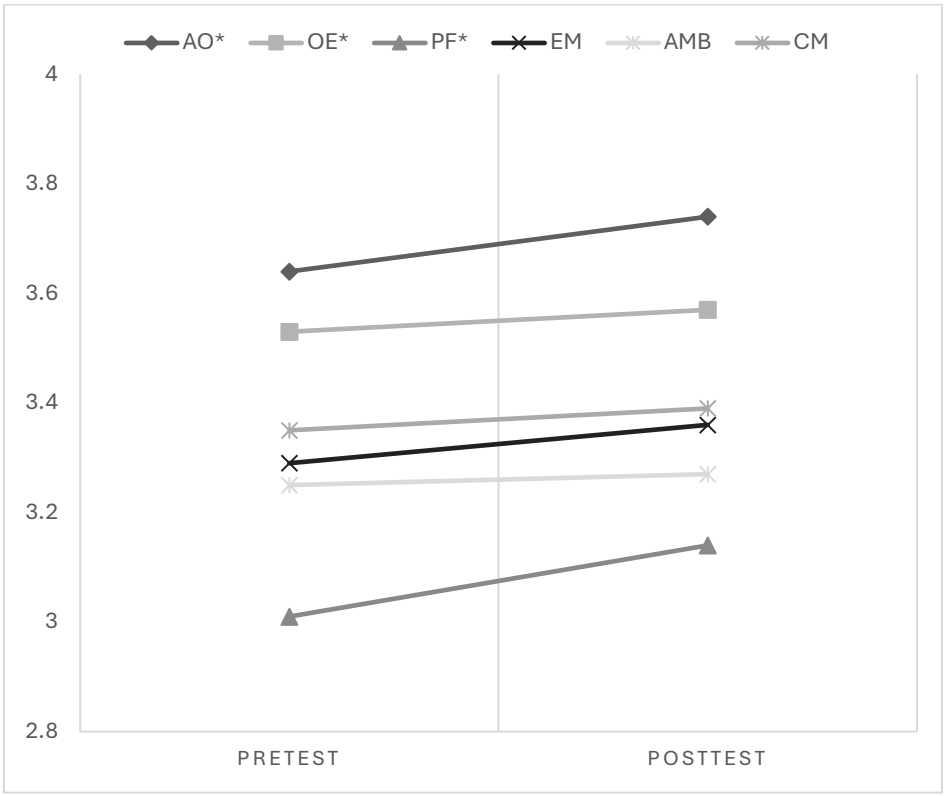
Deltas Between Pre- and Post-test and Within-Groups Differences

Deltas Between Pre-test and Post-test for the Whole Sample

We ran paired *t* tests for the whole sample between pre- and post-test to verify for significant differences between before and after the project management course. Results indicate significant and positive change for the three skill-based employability variables (A&O: $t = 6.27$; $p < .001$; OE: $t = 2.09$; $p = .037$; PF: $t = 4.76$; $p < .001$). For OE, we observe a very small difference (M = .03; SD = .58), whereas for A&O and PF the differences are M = .11; SD = .61 and M = 0.13; SD = .99, respectively. External marketability, career ambition and career motivation do not yield significant change ($p > .05$).

Figure 1

Evolution Between Pre- and Post-test for Each Measured Variable



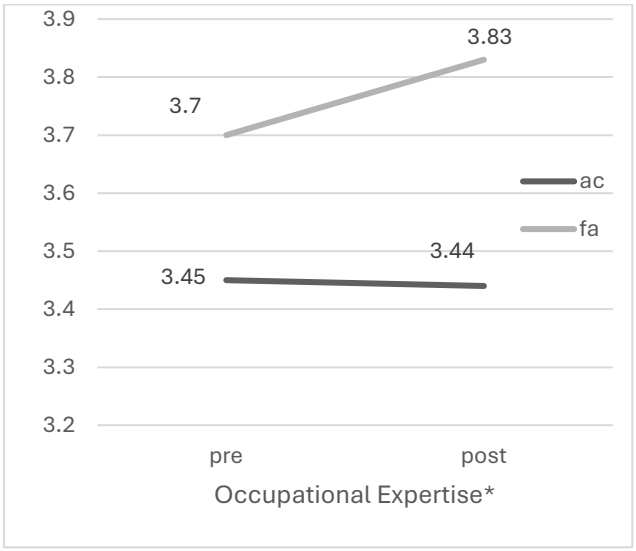
$^{*}p < .05$

Within-Groups Differences Between Pre- and Post-test

To verify for a status effect (academic cohort *vs*. free audit participants), we ran a repeated-measure ANOVA for each research variable, fixing status as a between-subjects factor. For the skill-based factors, we found a significant status effect for OE (Wilks' λ = .987; $p < .001$), with the larger difference within free audit participants (FA): M = .13; SD = .01. No significant effect of status was found for O&A and for PF ($p > .05$).

Figure 2

Evolution of Occupational Expertise Between Pre- and Post-test by Group

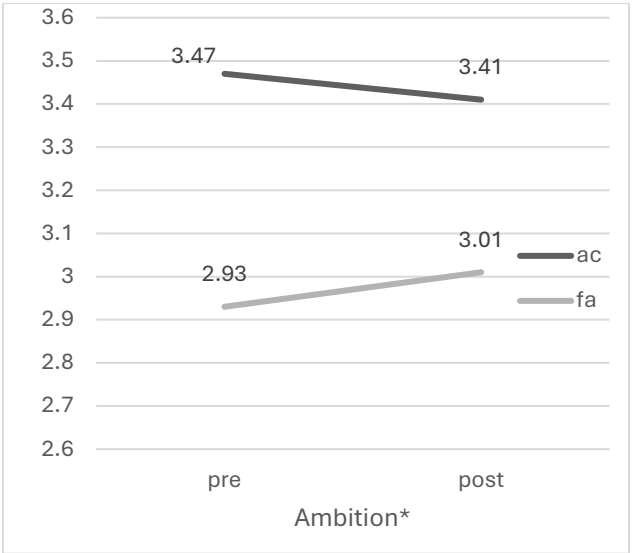


*$p < .001$

As for career self-perception variables, we found a significant effect for AMB: Wilks' $\lambda = .994$; $p = .006$, with the largest difference in favor of FA: M = .12; SD = .02. No significant changes by status membership were observed for EM and CM ($p > .05$).

Figure 3

Evolution of Career Ambition Between Pre- and Post-test by Group



*$p < .01$

Discussion

Table 5 offers a synthetic overview of the main findings, showing how they connect to our research questions, conceptual framing and the existing literature on employability.

Table 5

Summary of Findings and Links with Literature and Theoretical Concepts

Research question(s)	**Key empirical finding**	**Link with literature**	**Contribution to conceptual framing**	**Theoretical implication**
RQ1, RQ2 (AC *vs*. FA)	- Dispositional employability: AC > FA. - Skills-based employability & career motivation: FA > AC. - Difference between AC and FA are constant over time.	- Demonstrability of transferable skills and experiences (Rothwell & Arnold, 2007) - AC display more optimistic career-related perceptions (Rothwell, Herbert & Rothwell, 2008). - dispositional measures: may overlap broader self-concepts constructs (Berntson et al., 2008; Vanhercke et al., 2014).	Reinforces the distinction between skills-based and dispositional employability and shows that different learner groups position themselves differently on these two dimensions.	- Employability profiles appear group-specific: in MOOC contexts, employed participants primarily capitalize on skills and experience, while students mobilize more attitudinal and aspirational resources. - Relying exclusively on dispositional measures may overestimate employability by capturing self-concept rather than labor-market-relevant resources.
RQ3 (overall change over time)	- Changes in skills-related employability > dispositional constructs linked to individual career self-management.	- Distinctions between "hard" employability assets and broader career self-perceptions (Hillage & Pollard, 1998; Fugate et al., 2004; Miller et al., 2013).	- Competence-based employability: the most proximal outcome of a project-management MOOC - Dispositional employability functions: a more stable background orientation.	In MOOC studies: prioritize skills-based indicators for detecting short-term change and treat dispositional employability as a slower-moving construct.
RQ4 (change over time AC *vs.* FA)	- Differences between AC and FA are not uniform across all sub-dimensions - Significant improvement only for FA (skills-based & dispositional).	FA use online training to update immediately applicable competences (Forrier et al., 2015; Dillahunt et al., 2016).	A short, focused MOOC is more likely to shift skills-related indicators and, for employed learners, can also reinforce career-related attitudes.	MOOCs function as a form of targeted professional development for participants already embedded in the labor market, while students appear to stabilize rather than transform their employability perceptions over such a short time frame.

** AC: Academic cohorts; FA: Free Audits*

Theoretical Implications

The results of this study highlight distinct patterns in employability development between academic cohorts (AC) and free auditors (FA). AC consistently outperform FA in dispositional employability, i.e., in career self-perception, specifically in external marketability and career ambition, both before and after the MOOC. Conversely, FA demonstrate higher levels of skill-based employability, more precisely in occupational expertise and anticipation and organization, while also surpassing AC in dispositional employability related to career motivation. For both groups, these differences remain stable across pre- and post-test measures. However, significant evolution is observed only among FA, who improve in two subdomains of both approaches of employability, namely in occupational expertise and career ambition, over the course of the MOOC. This suggests that while AC maintain higher dispositional employability across both tests (only on two constructs), FA benefit more from the MOOC in terms of specific skill development but also in terms of career attitude.

When considering the whole sample, the online training program in project management yielded a higher effect on skills-related employability than on self-perception constructs linked to the individual career: The explanation could be in the operationality of occupational expertise, anticipation, and organization dimensions and personal flexibility (hence not directly linked to the career management and career self-perception *per se*), of the PM MOOC comprising units about project planification and management. It is therefore not surprising to find skills-related variables yielding significant positive changes between Week 1 and Week 4 of the course. However, when dividing the sample, we found that only FA significantly evolved in terms of occupational expertise, as mentioned earlier.

The finding that free participants, already active in the labor market ("dominated by demonstrable transferable skills and experiences" Rothwell & Arnold, 2007, p. 37) and possessing prior work experience, exhibit higher levels of skill-based employability is consistent with expectations (Forrier et al., 2015). In contrast, university students display more pronounced career-related perceptions, particularly regarding career ambition and external marketability (Rothwell et al., 2008). This divergence suggests that while free enrollees are more adept at critically evaluating the alignment of their competencies with market demands, university students may tend to overestimate their employability. The elevated ambition observed among students can be interpreted as reflective of a generally optimistic outlook, possibly influenced by their relatively limited exposure to the practical realities of the job market (Hillage & Pollard, 1998; Fugate et al., 2004). These findings echo those of Rothwell and Arnold (2007), who found that non-graduates felt slightly more employable than graduates. As a possible explanation, the authors propose that this finding may indicate that some already employed subjects have internalized concerns that the rapid expansion of higher education is resulting in an oversupply of graduates relative to the available positions. In our research this could have been translated into a more "optimistic" self-evaluation of their own dispositional employability by university students (in our case, graduate students enrolled in masters' programs).

One might argue that individuals already active in the job market *should* perceive themselves as more employable than graduate students. This is supported by our study, which revealed that such individuals express higher levels of skills-based employability (*i.e.,* occupational expertise, anticipation, and organization) that are closely linked to practical work experience (Forrier et al., 2015; Dillahunt et al., 2016). Conversely, graduate students reported higher levels of dispositional employability (except in career motivation), highlighting the theoretical distinction between these dimensions, in line with previous work.

For instance, Tomlinson (2007) found that, in a fast-evolving job market demanding flexibilization and individualization, "students appeared to be concerned with the need to adopt a more flexible and adaptive approach to careers, involving the active management of their own employability," p. 288). While the skills-based approach is pragmatic and directly associated with tangible job experience (Miller et al., 2013; Rothwell et al., 2008), the dispositional approach reflects attitudinal factors, such as external marketability and ambition, which are not necessarily contingent on the "real-world" labor market dynamics (Hillage & Pollard, 1998; Fugate et al., 2004).

We also propose another possible explanation of our results: The fact that graduate students tend to express higher levels of self-perceived employability suggests that our measures may capture not solely self-perceived employability, but also broader individual dispositions and self-concepts for this population. Thus, only evaluating employability from a dispositional perspective may raise the risk of evaluating a self-concept rather than a targeted assessment of employability: For instance, Berntson et al. (2008), underline that "perceived employability and self-efficacy are distinct from, yet related to one another" (cited by Vanhercke et al., 2014, p. 595). Consequently, research should systematically adopt a dual approach when measuring employability: Incorporating both skill-based and dispositional frameworks will help discern which segments of the population exhibit greater emphasis in specific aspects of employability. For instance, a study on employers' expectations about graduates' employability, found that "professional maturity is the dominant factor considered by employers when assessing graduate student employability" (Chhinzer & Russo, 2018, p. 117).

Although the skills themselves are measurable, how individuals assess their marketability is largely determined by internal dispositions, hence, as suggested by our results, external marketability is more closely aligned with dispositional employability. Additionally, we found that external participants overperformed graduate students in skills-based approach employability, but also in career ambition, and no differences between both groups were observed for personal flexibility, a sub-dimension of employability skills. A possible explanation lies in the somewhat overestimated permeability between both approaches. Indeed, Vanhercke et al. (2014) underline that "there is some overlap between the competence-based and the dispositional approaches, particularly at the measurement level" (p. 596), as they both reside at the psychological, subjective levels.

Practical Implications

The practical implications stemming from this study point toward using MOOCs for promoting employability. First, in terms of MOOC design and integration within formal education, universities should continue embedding flexible, modular courses that incorporate interactive elements and micro-credentialing systems to complement traditional curricula. Such an approach not only helps validate students' learning through digital badges and certificates (Dillahunt et al., 2016; Yuan & Powell, 2013) but also helps aligning academic content with current labor market demands.

Second, a strong collaboration between employers and educational institutions can leverage MOOCs as cost-effective tools for ongoing professional development. If MOOC content is closely aligned with job-specific requirements, it receives stronger support from employers, particularly for enhancing practical competences needed in both internal and external labor markets (Hamori, 2017; Torrent-Sellens et al., 2016), and can therefore help reducing the graduate skills gap noted in recent literature (Santandreu Calonge & Shah, 2016;

Monteiro et al., 2022). As shown in the present study, both graduate students and active populations can benefit from such for-credit open format university courses.

Third, in light with the results of this research underscores, it would be interesting to tailor MOOC content to different learner groups (in this case, free auditors and academic cohorts). Importantly, our findings show potential to be leveraged in two distinct ways: first, MOOCs can be used to foster positive and proactive dispositions among students by reinforcing self-concept and career identity, and second, they can respond to the active population's need to develop transferable skills that enhance employability in both internal and external job markets. Thus, a dual approach, integrating both skill-based and dispositional measures, can provide a more nuanced understanding of how different groups perceive and enhance their employability (Fugate et al., 2004; Monteiro et al., 2022; Römgens et al., 2020). This differentiated approach allows educators and employers to design interventions that are specifically calibrated to the needs of each subgroup, ensuring that MOOC content not only equips learners with practical knowledge but also cultivates the motivational and attitudinal dimensions essential for successful career development.

Limits and Future Research

While this study offers valuable insights into the impact of MOOCs on self-perceived employability and career self-perception, there are several limitations to be pointed out. Methodologically, sample attrition may have influenced the stability and representativeness of the results. Additionally, the use of a convenience sample combined with voluntary participation in the questionnaires may have introduced a self-selection bias: Respondents are likely to be more motivated, more engaged in the MOOC, or more confident in their skills than non-respondents. As a result, the patterns observed should be interpreted as reflecting the perceptions of this engaged subgroup rather than as representative estimates of the entire PM MOOC population or of MOOC learners more generally, which further constrains the generalizability of our findings. A key limitation of the present study is also the absence of a control group that did not receive the MOOC intervention. This design makes it difficult to rule out rival explanations for changes observed in employability perceptions or career development outcomes, such as natural maturation effects, prior career engagement, or self-selection biases. Future research should address these limitations by employing longitudinal and mixed-methods approaches that capture both subjective perceptions and objective indicators of employability, and by incorporating more diverse samples to enhance external validity. Future research should also replicate this design in MOOCs from other disciplinary fields beyond project management, in order to examine whether the employability patterns observed here generalize across academic subjects and learner populations. Lastly, refining measurement tools to distinguish between dispositional factors and skills-based outcomes will be essential for developing a more nuanced understanding of how MOOCs contribute to career development and for informing targeted interventions that better align educational practices with labor market demands.

Declarations

Availability of Data and Material

The datasets used and/or analyzed during the current study are available from the corresponding author upon request.

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Appendix

Used scales (items with a "*" were adapted to fit both working individuals and students):

Competence-based and multi-dimensional measurement of employability (adapted from Van der Heijden et al., 2018) :

Occupational Expertise

During the past year, I was, in general, competent to perform my work accurately and with few mistakes.

During the past year, I was, in general, competent to take prompt decisions with respect to my approach to work.

In general, I am competent to distinguish main issues from side issues and to set priorities.

I consider myself competent to weigh up and reason out the "pros" and "cons" of particular decisions on working methods, materials, and techniques in my domain*.

How would you rate the quality of your skills overall?

Anticipation & Organization

I spend much time improving the knowledge and skills that will be of benefit to my work or future work*

I consciously devote attention to applying my newly acquired knowledge and skills.

During the past year, I was actively engaged in investigating adjacent job areas to see where success could be achieved.

During the past year, I associated myself with the latest developments in my job domain.

Personal Flexibility

How easily would you say you can adapt to changes in your domain?*

How quickly do you generally anticipate and take advantage of changes in your environment?*

How much variation is there in the range of duties you aim to achieve in your domain?*

Career Self-Perception:

External Marketability (from Rothwell and Arnold, 2007 and Rothwell et al., 2009)

I can easily find out about opportunities in my chosen field

The skills and abilities that I possess are what employers are looking for

People in the career I am or aiming for are in high demand in the external labour market*

Anyone with my level of skills and knowledge will be highly sought after by employers*

I could get any job, anywhere, so long as my skills and experience were reasonably relevant.

Career Ambition (from Rothwell and Arnold, 2007)

I want to be in a position to do mostly work which I really like

I am satisfied with the progress I have made meeting my goals for the development of new skill

I have clear goals for what I want to achieve in life

I regard myself as highly ambitious

I feel it is urgent that I get on with my career development

What I do in the future is not really important (reverse-scored)

Career Motivation: Career insight subscale (from Noe, Noe and Bachhuber, 1990)

To what extent . . .

. . . do you have a specific career goal?

. . . do you have a specific plan for achieving your career goal?

. . . do you feel you are aware of your skill strengths and weaknesses?

. . . have you changed or revised your career goals based on new information you have received regarding yourself or your situation?

Competencies for Online Teaching Assistants: Integrating Technology, Pedagogy, and Communication Skills

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Abstract
The integration of information and communication technologies in higher education has transformed online learning, however, challenges such as low course completion rates, limited learner engagement, and insufficient interaction persist. This study aims to develop a competency-based framework for teaching assistants in fully online universities, focusing on their role in facilitating engagement and interaction within Learning Management Systems. Grounded in a constructivist–interpretivist paradigm, the study used a qualitative approach and reflexive thematic analysis of interviews with 15 experienced TAs and 7 faculty members. Data analysis, guided by the Technology Acceptance Model 2, Social Interaction Theory, and Connectivism Learning Theory, revealed four main themes (1) professional-technical, (2) ICT (thinking, knowledge, skills), (3) interaction & classroom management, and (4) meta-professional, comprising 12 subthemes. The framework emphasizes subject matter expertise, research support, instructional facilitation, ICT skills, communication and collaboration, managing student behavior, strategic insight and intuition, creativity and innovation, and ethical and moral competencies. The study contributes to the understanding of the complex roles of TAs in digital higher education and provides actionable insights for optimizing their training and utilization in online learning environments, ultimately enhancing the quality and accessibility of online education.

Keywords: Competency-based framework, interaction skills, online learning, professional development, qualitative research, teaching assistants

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Despite growing recognition of teaching assistants' (TAs) critical contribution to online learning (OL), existing scholarship lacks a comprehensive framework that specifies the precise roles and competencies TAs require in fully online institutions. Most prior research has focused on TAs in on-campus or blended learning contexts—examining program design (Boman, 2013; Brent & Felder, 2008), student outcomes (Crowe et al., 2014), and professional development (Ciston et al., 2016). Moreover, Wadams and Schick-Makaroff (2022) observed, the roles, responsibilities, and development strategies of TAs in online, MOOC, and blended-synchronous environments remain highly varied and often insufficiently defined or coherently articulated.

For clarity, in this study a TA is defined as a graduate student who, under the formal supervision of the course instructor, assumes responsibilities that support the delivery of an online course.

The incorporation of information and communication technologies (ICTs) has fundamentally transformed higher education, positioning online learning (OL) as a primary modality for instruction. As Bartoletti (2016) notes, OL affords students unparalleled access to resources, peer collaboration, and instructor engagement—regardless of temporal or geographic constraints. Yet, despite these advantages, OL continues to grapple with limited learner engagement and insufficient interaction, factors that compromise both its efficacy and sustainability (Rai & Chunrao, 2016).

In this study, we define OL as any instructional activity delivered via digital platforms in which instructors and learners do not share a physical space simultaneously. Within this broad category, two main modalities emerge: (1) Synchronous learning, in which teaching occurs live through video conferencing—facilitating real-time dialogue and immediate feedback—and (2) asynchronous learning, where students engage with pre-recorded lectures, readings, or assignments at their own convenience, without the necessity of simultaneous participation.

Overcoming the engagement and interaction challenges inherent in OL requires more than sophisticated technological tools; it demands innovative pedagogical approaches. While discussion forums and video lectures can support both synchronous and asynchronous delivery, these tools alone often fall short of meeting learners' complex needs in digital environments (Arinto, 2016). Accordingly, human facilitation—most notably by TAs—is indispensable. As McHenry (2021) argues, TAs act as vital conduits between instructors and students, fostering personalized interactions, delivering timely feedback, and orchestrating collaborative activities (Bourelle et al., 2015). To fulfill these multifaceted roles, TAs must command a diverse skill set, encompassing technical fluency, pedagogical acumen, and effective communication (Mayer & Sekayi, 2018).

The TA's role is primarily supportive and operational. TAs possess subject-matter competence and assist learners, facilitate instructional activities, and carry out operational tasks; however, ultimate responsibility for course design, learning outcomes, and final grading generally remains with the instructor (Wadams & Schick, 2022; Park, 2004; Goodwin et al., 2021). Unlike instructors—who design course structures, set summative learning objectives, and make final grading decisions—TAs primarily provide operational facilitation, formative feedback, and sustained learner support (Wheeler et al., 2017).

Existing theoretical constructs—such as Socio-Cultural Theory (which elucidates how TAs can scaffold learning but does not guide virtual tool selection), the Technology Acceptance Model2 (TAM2) (Venkatesh & Davis, 2000) (which clarify technology adoption, social influence, and cognitive–instrumental factors yet may overlook pedagogical alignment), the Community of Inquiry framework (which describes online presence but does not address asynchronous facilitation), and Connectivism (which emphasizes network building but underrepresents source-evaluation strategies)—each illuminates isolated facets of TA practice without integrating them into a coherent, context-specific model. Consequently, institutions lack evidence-based guidance for recruiting, training, and deploying TAs in asynchronous, LMS–driven environments.

Unlike adjunct or full-time instructors who design and manage entire courses, TAs primarily support facilitation, student interaction, and formative feedback within instructor-designed structures. Therefore, preparing TAs for online environments requires distinct, practice-oriented, and competency-based training that differs fundamentally from faculty development programs.

By synthesizing and extending these theoretical lenses into a concise competency framework, the present study addresses this critical gap. We propose a structured model that identifies the technical, pedagogical, and interpersonal competencies TAs need to support students effectively in asynchronous learning contexts. Recent research on sequenced learning—often referred to as spacing and interleaving theory—suggests that well-designed asynchronous courses can engender high student satisfaction (Versteeg et al., 2020; Varkey et al., 2023).

At the same time, Fernandez et al. (2022) warn that the abundance of written assignments in asynchronous formats may impose a significant cognitive load, thereby highlighting the imperative of rigorous instructional design and robust TA support. In response to these findings, our framework explicitly outlines how TAs can alleviate cognitive burden and foster deeper engagement within LMS environments.

By foregrounding the predominant features of asynchronous learning, we offer a practical blueprint for institutions striving to refine TA training and deployment. This framework not only elevates the role of TAs in OL but also contributes to global efforts to improve the quality and accessibility of online education. Importantly, the framework is not merely a theoretical synthesis. It was developed from expert interview data and through an iterative (adaptive/reflexive) coding process, so it is grounded in theory and reinforced by field-derived insights from both teaching assistants and faculty with extensive TA supervision experience.

This study's primary innovation is the development of a competency-based framework tailored specifically to the operational and facilitative role of TAs in fully online higher education institutions that rely on LMS platforms.

The primary aim of this study is to propose a competency-based framework for TAs in fully online universities—one that emphasizes their facilitation of interaction and engagement within LMS settings and, specifically, addresses the following research question:

What are the core competencies TAs require to effectively facilitate interaction and student engagement in LMS-based asynchronous online courses, and how should those competencies be structured into an operational framework for TA selection, training, and evaluation?

Review of Literature and the Theoretical Lens

The role of TAs in higher education has transformed markedly, especially within fully OL environments. Across the United Kingdom and North America, it is now commonplace for doctoral candidates and graduate students to support undergraduate instruction (Arshavskaya, 2015; Webster et al., 2011). Although this model capitalizes on TAs' disciplinary expertise and fosters their professional development, concerns persist regarding their preparation and efficacy—concerns that become particularly acute when face-to-face interaction is replaced by digital mediation (Bourelle et al., 2015; Winter, 2015; McHenry, 2021). In these virtual contexts, TAs must not only possess content knowledge but also develop the ability to facilitate learning via technology and cultivate productive online social interactions.

Recent studies underscore the complementary contribution of TAs to widening access, strengthening engagement, and improving the overall quality of learning. This supplementary role commonly involves leading practice or laboratory sessions, providing formative/process-focused feedback, facilitating discussions, and managing routine technical and administrative issues; formal occupational descriptions likewise highlight these supportive and instructional functions (U.S. Bureau of Labor Statistics, 2020). Empirical evidence indicates that TA presence—particularly in large-enrollment contexts and in laboratory-intensive units—increases instructional responsiveness and makes possible small-group or one-to-one interactions that are crucial for deep learning (Crowe et al., 2014).

The literature also consistently documents practical and structural distinctions between the responsibilities of instructors and those of TAs. Instructors are typically accountable for course design, learning-outcome specification, and summative assessment decisions, whereas TAs tend to focus on operational tasks: running sessions, delivering day-to-day feedback, and monitoring students—especially those at risk of falling behind. Because TAs are generally more accessible, this division of labor allows them to play a key role in enhancing student engagement and satisfaction when instructor presence is limited (Wheeler et al., 2017). Moreover, accumulating evidence suggests that TA support can positively influence student persistence—particularly among underrepresented groups—by fostering sustained contact and a stronger sense of belonging within the program (Wheeler et al., 2017). Complementing this body of evidence, the study by Li et al. (2024) found that MOOC teaching assistants develop a distinct set of online-specific competencies—including adaptive linguistic mediation for intercultural communication, self-efficacy in online communication, critical reflective practice, and capacities for digital civic engagement—that enable them to perform both supportive and pedagogical roles at scale.

Moreover, Wadams and Schick-Makaroff's (2022) integrative review, based on a systematic examination of the literature, offers evidence that the roles, responsibilities, and professional-development strategies of TAs differ across three instructional models—fully online courses, MOOCs, and synchronous blended environments—and are often not clearly defined.

The review further shows that most existing professional development interventions take the form of on-the-job training, whereas structured, purposefully designed programs with systematic evaluation are comparatively rare (Wadams & Schick-Makaroff, 2022).

Along similar lines, the mixed-methods empirical study by Ntourmas et al. (2022), which employed content analysis, qualitative interviews, and social-network analysis, investigated TAs' facilitative behaviors within the discussion forums of two MOOCs to assess how they support learner engagement using the Community of Inquiry (CoI) framework as the benchmark for MOOC instructional quality. The study found that TAs frequently provide rapid, direct answers instead of guiding learners through exploration, reflection, and problem solving—an outcome that reveals a meaningful gap between actual TA practice and the facilitation expectations implied by the CoI framework. (Ntourmas et al., 2022).

Building on this evolution, previous research has employed several theoretical frameworks to illuminate distinct facets of TA effectiveness, yet none offers a fully integrated explanation tailored to wholly online settings.

First, Vygotsky's socio-cultural theory (1978) casts TAs as more knowledgeable others (MKO) responsible for scaffolding student learning within the Zone of Proximal Development (ZPD). In traditional or blended classrooms, this role often involves circulating among small groups or posing probing questions to deepen understanding (Gardner & Jones, 2011). In online environments, TAs must replicate that support through discussion forums, annotated feedback, and live video sessions. While the socio-cultural lens underscores the importance of guided interaction, it does not specify which digital tools most effectively mediate these exchanges or how TAs can systematically develop online scaffolding techniques within a learning management system (LMS).

Second, TAM2 (Venkatesh & Davis, 2000) extends the original Technology Acceptance Model by showing that, beyond perceived usefulness and perceived ease of use, social-influence processes (e.g., subjective norm, voluntariness, and image) and cognitive–instrumental factors (e.g., job relevance, output quality, and result demonstrability) shape perceived usefulness. This application of TAM2 aligns with systematic reviews of faculty adoption of online teaching, which find that TAM2 constructs offer a coherent, evidence-based lens for understanding instructors' attitudes toward online course delivery and technology use (Wingo et al., 2017). Applied to TAs, TAM2-based studies show that those who recognize LMS features—such as analytics dashboards or integrated chat tools—as pedagogically valuable are more likely to adopt them confidently (Mayer & Sekayi, 2018; Reeves et al., 2016). Yet TAM2's strength—its parsimonious account of user motivation—becomes a limitation in online pedagogy, where nuanced decision-making is required: TAM2 alone does not explain how TAs align particular tools with specific learning objectives or manage the complex social dynamics inherent in collaborative digital settings.

Third, the Community of Inquiry framework (Garrison et al., 1999) posits that effective online learning emerges from the interplay of cognitive presence (learners' construction of meaning), social presence (comfort in expressing authentic selves), and teaching presence (instructional design and facilitation). Research shows that TAs, alongside lead faculty, support these three presences by moderating forums to build community, crafting discussion prompts to

stimulate critical thinking, and providing timely feedback that reinforces teaching presence (Bourelle & Rankins, 2015; Chickering & Gamson, 1987). Although this framework richly describes how interactional dynamics influence learning, it falls short of explaining how TAs make strategic technological choices—choices that fundamentally shape the spaces where cognitive, social, and teaching presences coalesce.

Fourth, Connectivism (Siemens, 2004) reconceptualizes learning as the process of forming and navigating networks of information and human connections. TAs who adopt a connectivist stance guide students to discover, evaluate, and integrate diverse digital resources—ranging from specialist blogs to online communities of practice—thereby supporting self-directed knowledge construction (Mayer & Sekayi, 2018; Rai & Chunrao, 2016). However, Connectivism's emphasis on broad network formation often lacks concrete guidance on how TAs coach novices to critically assess source credibility or reconcile conflicting perspectives within those networks.

Collectively, these theoretical perspectives reveal complementary strengths and important gaps, underscoring the need for an integrated, TA-specific competency framework tailored to fully online contexts.

Toward an Integrated Lens

Our research synthesizes these four theoretical perspectives to capture the multifaceted competencies TAs require when facilitating instructor-led course delivery and providing direct learner support in fully online courses. We begin by extending socio-cultural scaffolding to the digital domain: specifically detailing how TAs design LMS-based learning pathways—such as sequenced discussion prompts and structured peer reviews—to replicate ZPD-oriented support both asynchronously and synchronously. Next, we refine TAM2 by introducing the concept of ICT (define ICT) thinking, a reflective decision-making process wherein TAs weigh perceived usefulness and ease of use against pedagogical aims, selecting and evaluating digital interventions with instructional intent rather than technical convenience alone. Then, drawing on the Community of Inquiry, we identify concrete communication strategies—such as targeted questioning and dynamic facilitation—that TAs employ to sustain cognitive and social presence and to provide pedagogical support and facilitation in virtual classrooms. Finally, through the lens of Connectivism, we articulate how TAs coach students in constructing and navigating online knowledge networks, including practices for verifying information credibility and encouraging peer-to-peer exchanges.

By weaving these strands together, our integrative framework posits that effective TA performance relies on three intertwined capabilities: (1) scaffolded content expertise (socio-cultural theory), (2) strategic ICT proficiency (refined TAM2), and (3) interactional facilitation (Community of Inquiry), while also guiding networked learning (Connectivism). This synthesis advances theoretical understanding by illustrating how TAs enact these models in practice—for example, using ICT thinking to scaffold ZPD growth, which fosters more meaningful social interaction and broadens students' digital networks.

Methodology

Research Paradigm

This study is rooted in a constructivist and interpretivist paradigm, which aligns with its qualitative research design. This paradigm emphasizes the collaborative construction of knowledge through meaningful engagement with experts and stakeholders, reflecting the subjective and context-dependent nature of competencies required for TAs in digital higher education. By employing this constructivist framework, the research approach—covering both data collection and analysis—was tailored to capture the diverse perspectives of experts. This ensures that the resulting competency model accurately represents the complex and dynamic realities of TAs' roles in digital universities (Creswell, 2015).

Method

The study adopted a constructivist, theory-guided qualitative approach to generate in-depth, expert-informed thematic insights and to explore emergent elements of consensus (Creswell, 2015). Data were collected via purposive expert sampling and semi-structured interviews and were analyzed using reflexive thematic analysis (Braun & Clarke, 2019).

Researcher Reflexivity

As the primary researcher, I bring a multidisciplinary background in digital higher education, with 10 years of experience as a TA and 2 years as an instructor at the fully online university. My interest lies in exploring the elements of quality assurance in OL, with a particular focus on the role of TAs as a critical component of this system. These experiences have provided me with valuable insights into the challenges and opportunities associated with TAs in digital education. While this background enriches the study, it may also shape the interpretation of findings. To minimize potential biases, I adhered to rigorous methodological practices, including peer debriefing, member checking, and maintaining transparency throughout data analysis and interpretation (Denzin & Lincoln, 2011).

Participants

Participants in this study included 15 experienced TAs and 7 faculty members who were selected through purposive and snowball sampling methods. The inclusion criteria were: (a) academic and professional qualifications (Ph.D. students or Ph.D. candidates), (b) a minimum of five years of teaching-assistant experience at the fully online university, (c) attainment of the highest student satisfaction ratings in assessments, and (d) possession of specialized knowledge and skills in ICT. It is worth noting that participants in our study were purposively drawn from a range of academic disciplines; therefore, the data reflect cross-disciplinary variation. Given the fully online nature of the university, participants were selected from individuals currently active at universities in Europe, the United States, and Canada, or from those pursuing a Ph.D. with international experience in the field of OL. Additional faculty members who had conducted capacity-building programs for TAs in fully online programs were also included.

Before each term, TAs are required to complete institutionally organized onboarding focused on the university's LMS and instructional procedures. This mandatory preparation combines hands-on workshops—such as professional ethics in online learning environments; data protection and student confidentiality (including policies on secure storage, responsible sharing, and the ethical use of learning data); academic integrity and misconduct policies; and a

code of conduct for online interactions that emphasizes professional interaction, mutual respect, and responsible communication—with step-by-step demonstrations of LMS tools, review of assessment rubrics and academic policies, and practical simulations of core TA tasks. Beyond pre-term training, TAs receive ongoing support through direct mentoring by course instructors, consultative pedagogical support units, and a technical helpdesk—mechanisms that together enable rapid resolution of technical issues, timely pedagogical guidance, and sustained professional development during the semester. These integrated supports ensure that TAs are well prepared to perform their primarily supportive and operational roles within online courses.

Recruitment was conducted primarily through formal and informal networks of teaching assistants. Specifically, an initial announcement was made during the TAs empowerment program, and additional invitations were disseminated across groups and networks where members routinely share professional experiences—including internal knowledge communities, discussion forums within the LMS, and professionally oriented social networks frequented by TAs. Access was further facilitated by the researcher's prior experience working as a TA; coordination with potential participants took place via the researcher's email and group-channel messages. All interested candidates received the study information and provided informed consent before their interviews.

Following thematic analysis, the research team observed that codes and core themes repeated and that further interviews generated few novel conceptual insights; this point of diminishing returns was treated as data saturation in accordance with qualitative methodological conventions. Consequently, sampling was discontinued after approximately 19 interviews; however, to safeguard disciplinary diversity and reduce the risk of omitting structured perspectives, three supplementary interviews were conducted (Guest et al., 2006; Patton, 2002), bringing the total to 22. Further details are provided in Table 1.

Table 1

Demographics Characteristics of Study Participants

Code	Participants	Experience years	Qualification	IT Skills	Subject Knowledge	Satisfaction assessment	Field of study	Location
1	TA	8	PhD Candidate (PC)	High (H)	VH	Satisfied (S)	Management	Canada
2	University professor (UP)	15	PhD degree (PD)	Very High (VH)	VH	Very Satisfied (VS)	Information Technology Management	London
3	TA	8	PC	VH	VH	VS	Economics	Iran
4	TA	11	PC	VH	VH	VS	Research Methods	US
5	UP	12	PD	VH	VH	S	Human Resource Management	Iran
6	TA	5	PhD Student (PS)	H	H	VS	Construction Engineering	Norway
7	UP	7	PD	VH	VH	S	Project and Management	South Africa
8	TA	10	PC	H	VH	VS	Educational Sciences	Iran
9	TA	11	PC	VH	VH	VS	Research Methods	Iran
10	TA	6	PS	VH	H	VS	Problem Solving	Iran
11	UP	15	PD	VH	VH	VS	Research Methods	US
12	TA	10	PC	VH	VH	VS	Business Administration	US
13	TA	6	PS	H	VH	S	Environmental Studies	Norway
14	TA	7	PS	H	H	VS	Higher Education	Iran
15	TA	11	PC	VH	VH	VS	Psychology	London
16	UP	20	PD	VH	VH	S	Higher Education	US
17	TA	7	PC	H	VH	S	Computer Engineering	Italy

18	TA	5	PS	H	H	VS	Industrial Management	Iran
19	UP	12	PD	VH	VH	VS	Social Sciences	Finland
20	TA	5	PS	H	H	VS	Project and Management	South Africa
21	TA	4	PS	VH	H	S	Management	Norway
22	UP	6	PD	VH	VH	S	E-Learning	Iran

Instrument

Drawing on a comprehensive literature review and anchored in four core theoretical frameworks—Vygotsky's socio-cultural theory, TAM2, the Community of Inquiry (social interaction theory), and Connectivism—a semi-structured interview guide was devised for this qualitative inquiry. The selected theoretical frameworks were used as sensitizing concepts in the development of the interview guide and to provide initial direction for the study; in other words, they helped delimit the study's focal areas while allowing participants' accounts to remain the primary source of analytic insight. The primary aim of this guide was to capture a wide range of perspectives from online TAs regarding the competencies they deem essential, spanning behavioral, ethical, and professional dimensions. Sources such as Park (2004), Miller (2001), Boman (2013), Meadows (2015), Rai and Chunrao (2016), Hardre and Burris (2012), Sohoni and French (2013), Bourelle and Rankins-Robertson (2015), Ciston and Went (2016), Reeves et al. (2016), Bubbar et al. (2017), Mayer and Sekayi (2018), and McHenry (2021) informed the design. To encourage both expansive input and eventual convergence, the guide paired an initial round of open-ended questions—inviting participants to elaborate freely—with a subsequent round of closed-ended items, aimed at building consensus around pivotal competency areas.

When crafting specific questions, each theoretical lens contributed uniquely. Drawing first on TAM2, we probed TAs' perceived usefulness and perceived ease of use of LMS and online instructional platforms (Miller, 2001; Park, 2004). For instance, participants were asked, as a teaching assistant, "Which technical features of the online platform have most effectively enabled you to support students?" and "What technical or conceptual obstacles have you faced when using digital tools to guide learners?" These inquiries reveal how assistants' attitudes toward technology shape their willingness and ability to employ these tools in ways that strengthen the teaching–learning dynamic.

In contrast, Vygotsky's social interaction theory highlighted the teaching assistant's role as a scaffolder within the virtual learning environment. Accordingly, questions were formulated to uncover how assistants leverage dialogue and feedback—whether in discussion boards or synchronous sessions—to expand students' ZPD (Boman, 2013; Bourelle et al. 2015; Meadows, 2015). Sample prompts included: "How have you used real-time feedback during online group discussions to reinforce student learning?" and "Which techniques have you adopted to manage collaborative, synchronous interactions in virtual spaces to support students in problem solving?" These items illuminate the active role of the assistant in nurturing social learning processes.

Moreover, Connectivism underscored the importance of an assistant's capacity to forge and manage digital knowledge networks that bolster student learning (Rai & Chunrao, 2016; Reeves et al., 2016; Mayer & Sekayi, 2018). To assess this competency, we asked questions such as, "Which online resources or communities do you recommend to students to deepen their grasp of course concepts?" and "How have you utilized specialized communication networks (e.g., topic-specific forums or messaging groups) to facilitate interaction between students and instructors?" Through these questions, we gauged the assistant's skill in guiding students toward credible online materials and fostering robust learning networks.

For the sake of clarity and organization, the interview guide's content was divided into two overarching sections: knowledge and practical skills. The knowledge portion addressed participants' awareness of general competencies—behavioral, ethical, and professional—expected of TAs. Meanwhile, the practical skills section encompassed questions regarding participants' proficiency in information technology and communication within an OL context (Ciston & Went, 2016; Hardre & Burris, 2012; McHenry, 2021; Sohoni & French, 2013). By weaving together these theoretical perspectives with the empirical literature, each interview question was intentionally constructed to capture—in a holistic and integrative fashion—the technological, social-interaction, and networking dimensions that define online teaching assistant competencies.

Procedure

The study was carried out at Mehralborz University, a fully online university. Prior to initiating the study, the research protocol and procedures were submitted to the Research Committee and the Human Resources Department to secure the necessary administrative approvals and coordination.

In this university, courses were primarily asynchronous and organized into weekly, module-based units. Each module combined pre-recorded lectures, forum-mediated community

activities, and project-based assignments. Class sizes typically ranged from 30 to 50 students, and the institution maintained an approximate TA-to-student ratio of one TA per 20 students.

The interview guide was organized into four sequential sections designed to move from contextual background to analytical reflection: (1) individual background (personal and professional context, discipline, course types, TA experience); (2) roles and practical duties (day-to-day tasks, facilitation practices, concrete examples of instructional and research support); (3) technology-related issues (tools and platforms in use, the role of ICT-oriented decision-making, familiarity with learning-analytics dashboards); and (4) behavioral and professional interactions (strategies for online class management, interpersonal dynamics, activity design, and management of student behavior). Each section opened with one or two broad, open-ended questions and used targeted probes to elicit situational examples, decision-making processes, and analytic reflections. Interviews concluded with a reflective summary aimed at identifying TAs' professional-development needs, training priorities, and policy recommendations. Participants were assured that no identifying information would be included in the study reports.

The interviews were conducted fully online via virtual platforms such as Skype. Participants' consent was recorded, and interviews lasted between 40 to 80 minutes. Participants were assured that neither their identities nor identifiable information would be used in the reporting of this study. Data collection took place between October 2022 and April 2023.

Data Analysis

To analyze the qualitative data obtained from interviews, the following systematic steps were undertaken (Braun & Clarke, 2006)

Data Coding and Categorization

Participants' interview transcripts were coded and categorized by two independent qualitative researchers (the study authors), both experienced in thematic analysis and online learning research. Responses were initially coded into meaningful units and grouped according to emerging patterns related to TA competencies in online learning environments. Data were analyzed using an iterative and adaptive coding process within a reflexive thematic analysis: initial inductive codes were generated from early transcripts, the codebook was refined through regular team meetings and joint-coding sessions, and codes were adapted as new patterns emerged. Throughout the analysis, the lead researcher maintained reflexive memos to document interpretive decisions and analytic developments.

Thematic Analysis

Coded data were further analyzed to identify patterns and common themes that reflected the participants' perspectives on core competencies.

Note on analytic stance: Although the interview guide was informed by selected theoretical frameworks used as sensitizing concepts, the analytic process itself began with inductive, reflexive procedures. Specifically, transcripts were read repeatedly and initial codes were generated from participants' actual language and experiences (inductive coding). The research team then engaged in iterative analytic meetings to refine codes and develop candidate themes; throughout this phase we maintained analytic memos and an audit trail to document decisions. In the final interpretive stage, the empirically derived themes were examined and compared against the sensitizing frameworks to identify points of convergence, divergence, and theoretical extension. This combined approach ensured that the analysis remained grounded in participants' accounts while benefiting from theoretically informed interpretation, and that potential researcher bias was managed via a transparent audit trail, documented reflective meetings, and member-checking.

Reflexive Coding and Researcher Consensus

To ensure analytic rigor, two authors independently engaged with the data and met regularly to discuss coding interpretations. Divergent readings were treated as opportunities for deeper reflection rather than reliability errors, consistent with the reflexive approach (Braun & Clarke, 2019).

Participant Feedback and Refinement

For member-checking we purposively invited seven participants (four TAs representing different disciplines and three faculty members) to maximize variation in discipline, role (TA vs. faculty), and relevant experience, and to include those whose interviews yielded particularly rich illustrative data. Selected participants received a concise analytic summary (theme descriptions, code definitions, and exemplar quotes) and were asked to comment on accuracy, omissions, and wording. Feedback was collected via e-mail and, when helpful, short video calls; suggested revisions were incorporated into the codebook and analysis. This iterative process continued until theoretical saturation was achieved, ensuring the robustness of the findings.

Theoretical Framework Integration

The analysis was guided by theoretical frameworks such as the TAM2, Social Interaction Theory, and Connectivism Learning Theory. These frameworks provided diverse perspectives, enabling nuanced interpretations of the competencies required for TAs in digital higher education.

The analysis began with a thorough reading of the transcripts to identify meaningful conceptual units. These units were systematically coded and grouped based on their similarities, differences, and alignment with key concepts. Categories and themes were then established, with relevant codes saturating each theme.

To enhance reliability, the first and second authors independently reviewed the transcripts multiple times to identify codes and categories. Initially, the authors collaborated on coding a single interview, discussing and resolving any discrepancies before proceeding with subsequent interviews.

In the second phase, the identified categories were organized into subthemes based on their meanings and alignment with the study's major concepts. This process resulted in a comprehensive map of codes, categories, and subthemes, ensuring an in-depth exploration of the data.

Subthemes were arranged under broader themes, with relevant quotations extracted and documented. The first draft of the results section was prepared by the lead author and shared with co-authors for review. Revisions were made based on their feedback, ensuring consistency, relevance, and the authentic representation of participants' voices. For anonymity, participants were referred to as P 1 to P 22 throughout the text.

Results

Based on the literature review, which incorporates insights from OL experts, our model comprises four main themes: technical-professional competencies, information and communication competencies, classroom management and teaching skills, and individual and general competencies. Within these themes, 12 sub-themes have been identified, each specifying important aspects pertinent to the competencies of TAs in the OL environment. We will now elaborate on each theme and its criteria. (See Table 2 and Figure 1.)

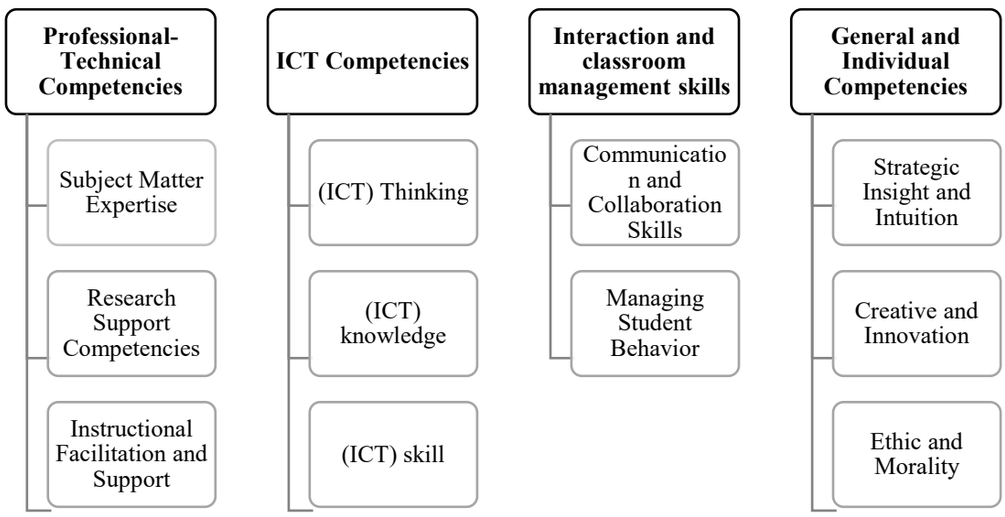
Table 2

Frequency of Identification of Themes and Sub-Themes in Literature and Interviews

Subthemes	Themes		Interview frequency	Total frequency
Subject Matter Expertise	Professional-Technical Competencies	8	12	20
Research Support Competencies				
Instructional Facilitation and Support				
ICT Thinking	ICT Competencies	6	18	24
ICT knowledge				
ICT skill				
Communication and Collaboration Skills	Interaction and classroom management skills	9	16	25
Managing Student Behavior				
Strategic Insight and Intuition	Meta-Professional Competencies	5	10	15
Creative and Innovation				
Ethical and Moral				

Figure 1

Conceptual Framework of Assistants' Competencies in OL Environment



Theme 1: Professional-Technical Competencies

In OL environments, the professional-technical competencies of TAs are critical for ensuring effective instruction and student support. Through extensive interviews with faculty members and TAs, three primary sub-themes were identified as essential components of these competencies: Subject Matter Expertise, Research Skills, and Teaching Skills. The literature in educational research supports these findings, emphasizing the pivotal role these competencies play in enhancing the OL experience.

Subject Matter Expertise (Mastery of Content Knowledge)

Subject Matter Expertise, or mastery of content knowledge, is crucial for TAs in OL environments. Participants 1, 5, 13, 16, 17, 18, and 22 emphasized the importance of this competency. One participant noted, "Mastery of course content, staying updated with new resources, and awareness of specialized topics in the field are essential for Tas" [P5, P17]. Another added, "Professional development and the ability to assist learners in accessing academic resources effectively are crucial" [P13, P22].

Research Support Competencies

In our study, research -support competencies refer to the foundational abilities and course-based support tasks that enable TAs to guide students in locating, evaluating, and utilizing open scholarly resources effectively in online learning contexts.

That emerged as a salient competency for TAs in online learning contexts, raised by eight participants [P2, P3, P4, P8, P10, P13, P18, and P22]. The data organize into two empirical subthemes:

Research Information Literacy. Participants described a cluster of foundational, research-oriented information skills—including targeted database searching, evaluation of source credibility, and guiding students to open-access resources and institutional digital libraries. Several respondents emphasized that many master's-level courses, while not formally "research methods" classes, incorporate project-based or collaborative research activities; in those contexts, TAs reported a clear need for baseline research competencies to help students find and use appropriate sources. Representative comment: "TAs must know how to use search tools, guide students in research projects, and recommend supplementary resources." [P10, P13, P22]

Practical Research-Support Tasks. A related set of activities concerned hands-on research support: assisting with the design of small studies or course projects, advising on data collection and analysis procedures, and supporting students with research writing conventions. One participant summarized this theme: "Distinguishing credible websites from non-credible ones and instructing students in how to prepare a research paper are key tasks" [P18].

Importantly, while eight participants mentioned research-related tasks, three of these respondents served as TAs in explicitly research-oriented courses (e.g., research methods or problem-solving seminars). Across the sample, participants consistently noted that ultimate responsibility for research design and summative assessment resides with the course instructor; nonetheless, they reported that TA competence in both research information literacy and practical research-support significantly enhances the TA's ability to support instructor-led, research-focused classroom activities.

Instructional Facilitation and Support. In this study, activities primarily aimed at achieving instructional objectives and enhancing content learning were coded under the theme Instructional Facilitation and Support. In other words, any reported action whose primary purpose was to improve students' conceptual understanding or skill proficiency—or to facilitate the completion of a specific learning task—was assigned to this category.

Many participants 1, 2, 3, 4, 5, 6, 8, 10, 12, and 14 emphasized the importance of instructional facilitation and support. For example, one participant shared, "small- and large–group instruction, continuous assessment, and ongoing evaluation are vital for effective teaching" [P3]. While another participant highlighted, "Knowledge sharing, collaborative teaching with professors, educational counseling, and continuous monitoring of student activities are essential components" [P12]. Moreover, one participant noted, "When I tie examples directly to course concepts, students clarify their thinking more rapidly" [P2; P8].

Thus, through targeted content facilitation within discipline-specific discussion forums—providing substantive content feedback, conducting formative assessments, guiding group assignments, implementing active learning exercises, drafting assessment questions and rubrics, and structuring scholarly discussions—TAs act as pivotal instructional supporters who bridge instructor intent and student learning, thereby consolidating the Instructional Facilitation and Support theme.

Theme 2: ICT Competencies

In the context of OL, TAs must possess a nuanced proficiency in information and communication technologies (ICT) that transcends basic technical literacy. Our interviews revealed three interdependent dimensions—ICT Thinking, ICT Knowledge, and ICT Skills—each grounded in well-established theoretical frameworks.

ICT Thinking

Our analysis revealed that TAs conceive ICT thinking not merely as technical skill but as a strategic decision-making process—the capacity to determine which digital tool to use, when to use it, and for what pedagogical purpose to address instructional challenges effectively. This process is closely linked to TAs' acceptance of and commitment to online learning: Positive beliefs about OL increase their motivation and willingness to adopt pedagogy-aligned digital solutions. Participants illustrated ICT thinking through concrete examples of tool selection and timing, emphasizing pragmatic fit over technical novelty. As one TA remarked, "Familiarity with the online environment and comfort with technology are essential for TAs" [P15; P17]; however, technical comfort alone does not suffice. As another participant observed, "Belief in and commitment to OL are essential for supporting students effectively in an OL environment" [P16].

In practice, ICT thinking might mean opting for synchronous video conferencing rather than an asynchronous forum when immediate clarification is required, engaging in metacognitive planning, or critically evaluating a tool's pedagogical fit. By framing instructional challenges, anticipating potential hurdles, and iteratively refining ICT-based solutions, TAs ensure that technology serves a clear pedagogical purpose rather than being applied arbitrarily.

ICT Knowledge

Complementing strategic reasoning, ICT knowledge embodies a declarative understanding of how digital infrastructures, software, and hardware function within online educational settings. Several participants emphasized its importance:

> Knowledge of hardware for example, the ability to configure and troubleshoot webcams, microphones, and headsets, and to manage a stable internet connection, on the software side, familiarity with LMS administration (e.g., Canvas or Moodle), video-conferencing

and screen-recording tools (e.g., Zoom, Teams), learning-analytics dashboards, and plagiarism-detection systems is useful for TAs [P10; P18].

Another TA also emphasized "Understanding circuit boards, processors, chips, electronic equipment, and ICT literacy is crucial" [P16].

Moreover, familiarity with interoperability protocols, data-security guidelines, and accessibility standards (e.g., WCAG) enables TAs to anticipate and address technical constraints proactively. Such concrete competencies enable TAs to provide timely, pedagogically aligned technical support within online courses.

ICT Skills

Finally, ICT skills encompass the hands-on abilities required to configure, customize, and troubleshoot digital tools. As one participant noted, "Basic technology skills and proficiency in using artificial intelligence tools are essential" [P2; P17], while another added, "Skills in managing discussion forums, chats, and interactive learning materials are crucial" [P11]. One TA reflected, "By monitoring online quiz analytics, I can reach out to struggling students before they fall behind" [P14]. Participants reported that practical technical tasks (e.g., embedding multimedia, setting up quizzes, generating grade reports) help integrate teaching, social, and cognitive elements and support student engagement [P10; P14; P19].

As Participant 19 observed, "Time management and planning in online environments, along with the ability to provide timely feedback using synchronous and asynchronous communication tools, are critical" [P19]. Yet several TAs and faculties caution that ICT skills alone are insufficient; they must be integrated with strategic ICT thinking and solid conceptual knowledge to yield meaningful pedagogical impact.

Theme 3: Interaction and Classroom Management Skills

Another crucial theme identified in this research is the competency of interaction and classroom management skills for TAs in the OL environment. This competency is essential for fostering effective interactions between students and the OL setting. It encompasses two critical sub-themes: Communication and Collaboration Skills, and Managing Student Behavior. These skills are vital for creating a supportive, engaging, and well-managed OL environment, ensuring that students can effectively interact with each other and the digital classroom.

Communication and Collaboration Skills

Effective communication and collaboration are pivotal in fostering a supportive and interactive OL environment. This competency involves collaborating with students, fostering motivation for cooperation and teamwork, and providing support to enhance learner morale. Participants 1, 3, 4, 7, 8, 10, 11, 13, 14, 15, 18, and 19 highlighted the importance of these skills. As one participant noted, "Flexibility and adaptability are crucial for TAs to effectively manage diverse student needs and dynamics" [P1; P18]. Another participant emphasized, "Effective communication skills and the ability to negotiate and interact within the team are essential for guiding and supervising teamwork" [P8; P15]. Moreover, one TA described how "gamified badges motivated students to help one another in the forum" [P3; P9]. Also, as Participant 10 stated, "Creating mutual trust and transparency in relationships with students enhances the learning experience and fosters a positive OL environment" [P10].

Therefore, TAs who excel in communication and collaboration can create healthy and constructive competition among group members, analyze and process group dynamics, and lead and direct students effectively.

Managing Student Behavior

Effectively managing student behavior in online classrooms is vital for sustaining a focused, respectful learning community. Our qualitative data and theoretical grounding reveal three interconnected strategies that TAs can employ to achieve this goal. First and foremost, we contend that establishing and communicating clear expectations lays the groundwork for student self-regulation and accountability. Consequently, before any activity begins, TAs should articulate precise norms—such as logging in punctually, remaining muted during lectures unless prompted to speak, and meeting assignment deadlines—to eliminate uncertainty around acceptable conduct. In practice, several of our interviewees mentioned displaying a Classroom Norms slide at the start of each module, which, as one TA explained, ensures that students know what is expected long before any issues emerge [P7; P20].

Moreover, building on these clear expectations, our findings suggest that TAs must actively monitor and promptly redirect to prevent minor disruptions from escalating. Some TAs mentioned that *during live sessions, they circulate through breakout rooms and scan discussion threads* to catch off-task chatter or irrelevant posts. When a student veered off-topic—perhaps by discussing unrelated matters in a group chat—a gentle redirection such as "Let's return to today's prompt" was sufficient to refocus attention without causing embarrassment [P4; P18; P9].

Finally, we emphasize that positive reinforcement and structured engagement activities help sustain desirable behaviors and promote deeper participation. Rather than relying solely on punitive measures, the TAs in our study praised exemplary behaviors—such as early assignment submissions or thought-provoking forum posts—thereby modeling the conduct they hoped to see replicated. Behavioral research confirms that such reinforcement increases the frequency of positive actions. Moreover, to address students' reluctance to participate, TAs introduced low-stakes reflection checkpoints and quick polls within asynchronous modules, requiring students to submit a brief, one-sentence insight before progressing. Although modest, these consistent prompts effectively reduced late submissions and fostered a shared sense of accountability.

Theme 4: Meta-Professional Competencies

Beyond specialized, professional, and ICT skills, TAs must develop meta-professional competencies that enable them to transcend routine tasks and proactively shape OL environments. Drawing on our interviews and established theory, we identify three interdependent dimensions: Strategic Insight and Intuition, Creativity and Innovation, and Ethical and Moral Competence.

Strategic Insight and Intuition

TAs who demonstrate strategic insight anticipate pedagogical and technological hurdles—such as waning discussion-board engagement or confusion over asynchronous tasks—before they escalate. They select LMS features (e.g., analytics dashboards, peer-review tools) to bolster perceived usefulness and ease of use. As one TA observed, "Having a clear vision and the ability to identify opportunities and threats helps me align support with broader course goals" [P1; P5]. Another added, "Self-leadership and strategic planning enable me to manage my tasks efficiently and support students more effectively" [P19; P21].

Consequently, TAs who cultivate systems thinking, critical reflection, and decisive action can enhance student engagement by providing timely, data-informed guidance, thereby fostering a more strategic approach to learning and problem-solving.

Creativity and Innovation

In our study, TAs recommended moving beyond conventional instruction by designing and implementing activities such as gamified assignments and structured peer-feedback processes. They noted that these practices foster student collaboration, enhance learner engagement, and support the co-construction of knowledge.

One TA remarked, "Creative thinking and the ability to embrace new ideas are crucial for developing engaging learning materials" [P3; P19], while another observed, "Innovative problem-solving helps me address technical barriers and enrich the learning experience" [P20; P8]. Several participants also reported experimenting with gamified assessments, micro-credential badges, and curated digital resources to broaden learners' networks and access to specialized materials. Also, as Participant 11 emphasized, creative activities such as "Structured peer-review tasks encouraged quieter students to contribute, which elevated overall discussion quality" [P11].

Ethical and Moral Competencies

Ethical and moral competencies form the foundation of a respectful, supportive OL environment. One participant noted, "Empathy and tolerance are crucial for building trust and rapport with students" [P1; P11], while another remarked, "Fair behavior and non-discrimination ensure all students feel valued and respected" [P12].

Furthermore, in practice, TAs vigilantly guard academic integrity by monitoring for plagiarism and coaching on proper citation, and they safeguard sensitive data—ensuring that grades and personal reflections remain accessible only to authorized stakeholders. When

facilitating group work, they remain alert to power imbalances or exclusionary behaviors, intervening to foster inclusive discussions.

Discussion

This study confirms and extends evidence that the practical role of TAs in fully online learning has expanded in scope and complexity. In particular, our findings show that TAs perform operationally distinct, pedagogically meaningful functions that differ from—and complement—the work of lead instructors. Whereas instructors remain principally accountable for course design, learning outcomes, and summative assessment, TAs operate as accessible facilitators who increase instructional responsiveness, personalize learner support, and help sustain continuity of learning across synchronous and asynchronous modalities (Crowe et al., 2014; Rafi et al., 2020). These functions not only relieve instructors' communication load but also enable personalized learning spaces that strengthen students' sense of belonging and reduce isolation.

We organize our interpretation around four interrelated competency domains identified in the analysis—professional-technical, ICT, interaction and classroom management, and meta-professional—and clarify how these domains map to complementary theoretical lenses.

Professional-Technical Competencies

Grounded in socio-cultural theory (Vygotsky, 1978), this domain emphasizes content knowledge and task-oriented instructional support. TAs who possess strong subject-matter expertise scaffold student learning through targeted explanations, worked examples, and formative guidance that extend learners' Zone of Proximal Development. Empirical work supports the pedagogical value of such scaffolding: TA-led facilitation deepens conceptual understanding and enhances learner confidence and persistence (Boman, 2013; Meadows et al., 2015). While core professional-technical skills are broadly transferable across disciplines, our data show discipline-specific tasks (for example, supporting research-methods activities) require additional, modular training. We therefore recommend competency frameworks that combine universal TA preparation with discipline-tailored modules.

ICT Competencies

Informed by TAM2 (Venkatesh & Davis, 2000), ICT competencies in our study combine strategic ICT thinking (deciding *when* and *why* to use a tool), declarative ICT knowledge (understanding platform affordances and constraints), and procedural ICT skills (implementation and troubleshooting). TAs who model confident, pedagogically aligned use of LMS features, multimedia authoring tools, and analytics dashboards reduce learner anxiety about digital tools and can intervene earlier with at-risk students, thereby improving engagement and retention (Mayer & Sekayi, 2018; Sohoni & French, 2013). Practically, this finding suggests TA training should go beyond "how-to" checklists and emphasize pedagogical alignment, analytics literacy, and routine troubleshooting workflows that enable timely, data-informed support.

From an integrative perspective, ICT thinking, knowledge, and skills form a cohesive triad that equips TAs to provide effective instructional support in online contexts. By weaving together metacognitive reasoning, theoretical frameworks, and practical proficiency, TAs not only resolve immediate technical issues but also anticipate future challenges—thereby enhancing student engagement, reducing technological barriers, and fostering a robust, adaptive online learning ecosystem.

Interaction and Classroom-Management Competencies

Drawing on the Community of Inquiry (Garrison et al., 1999), this competency cluster centers on sustaining cognitive and social presence through forum moderation, synchronous facilitation, and formative feedback. Our participants described concrete practices—establishing classroom norms, circulating between breakout rooms, using low-stakes reflections and quick polls, and structuring peer-review tasks—that keep learners focused, scaffold discourse, and raise overall discussion quality (Chickering & Gamson, 1987; Joksimović et al., 2015). These operational behaviors are distinct from content design: They are facilitative and regulatory, aimed at maintaining productive interaction and enabling self-regulation rather than re-designing curricular goals.

Meta-Professional Competencies

This domain—strategic insight, creativity, and ethical practice—integrates perspectives from Connectivism (Siemens, 2004), socio-cultural theory, and contemporary scholarship on mentorship and transparency (Bourelle & Rankins, 2015; Reeves et al., 2016). From a Connectivist stance, TAs function as node facilitators within students' learning networks, curating credible resources and coaching students to evaluate and synthesize digital information. Creativity (e.g., scenario-based simulations, gamified micro-tasks) expands learners' digital pathways and engagement, while ethical competencies (e.g., equity, data privacy, integrity monitoring) create the psychological safety necessary for intellectual risk-taking. When TAs intervene to remediate group-level power imbalances or to guard academic integrity, they foster environments where learners participate more fully and persistently (Hardré & Burris, 2012).

Integrative Synthesis

By explicitly linking each competency domain to theoretical perspectives, we clarify how TA capabilities translate into improved learning processes: Vygotskian scaffolding deepens conceptual mastery; TAM2-informed ICT proficiency reduces participation barriers; social interaction techniques heighten productive discourse; and connectivist strategies broaden learners' digital networks. Consequently, TA professional development should move beyond tool-training and adopt an integrated model that couples practical skill acquisition with theory-informed rationale.

Limitations

Several limitations should be considered when interpreting the findings of this study. First, the sample size was relatively small, comprising only 22 participants, which may restrict the generalizability of the results. The reliance on self-reported data collected through interviews introduces the potential for response bias, as participants might provide socially desirable answers rather than objective reflections of their experiences.

Furthermore, the study focused on a specific OL context within a single institution, which may limit the applicability of the findings to broader educational settings. Future research should include a larger and more diverse sample of TAs from various institutions and OL environments to validate and expand upon these results.

Although the thematic analysis, along with consensus-building procedures—specifically member checking and peer debriefing—facilitated the achievement of expert agreement, it may have constrained the depth of the qualitative data collected. Future studies could benefit from employing mixed-methods approaches to gain a more comprehensive understanding of the competencies required by TAs and their impact on online learning environments.

Conclusion and Implications for Practice

This study aimed to identify the knowledge and experience of TAs in enhancing the necessary skills required for their roles in a fully online university setting. In conclusion, the study has provided valuable insights into the pivotal role and essential competencies of TAs in OL environments. TAs play a crucial role in facilitating student engagement, supporting learning processes, and addressing the unique challenges associated with online education. The findings underscore the necessity for TAs to possess a balanced combination of technical proficiency, pedagogical expertise, and communication skills to fulfill their roles effectively.

Higher educational institutions should prioritize the professional development of TAs by implementing targeted training programs that specifically address the demands of OL. By equipping TAs with the requisite skills and knowledge, institutions can significantly enhance the quality of OL courses and ensure improved educational outcomes for students. Practical implications include the ongoing evaluation and enhancement of TAs training programs, the promotion of collaborative learning environments, and the utilization of theoretical frameworks to guide the development of effective OL strategies. Addressing these areas will not only enhance the effectiveness of TAs but also contribute to the overall success of OL initiatives within educational settings.

Higher education institutions can operationalize the proposed framework by developing competency-based modules (e.g., online pedagogy, LMS proficiency, formative assessment, and accessibility), delivering blended workshops that include facilitation simulations, and maintaining professional portfolios to document TAs' performance evidence. Issuing micro-

credentials for completed modules and involving TAs in course-design meetings helps align TA responsibilities with course learning objectives and formalizes skill recognition. For online supervision and evaluation, we recommend competency-aligned objective rubrics, multi-source assessment (student feedback, recorded-session review or peer observation, self-assessment, and supervisor appraisal), and regular formative feedback cycles. The ethical use of learning analytics as supplementary evidence, combined with linking evaluation results to targeted professional development plans, can accelerate TA performance improvement. Future research should examine the framework's validity and transferability across disciplines and cultural contexts and use cross-sectional and longitudinal designs to evaluate the impact of framework-based TA training on student learning outcomes and retention.

Declarations

Ethics Statement

According to the guidelines of the University of Tehran, this type of research did not require formal ethics approval.

Funding Statement

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AI Use Statement

Generative artificial intelligence (AI) was used in the preparation of this manuscript for grammar refinement using Grammarly. 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 authors, who take full responsibility for the accuracy and integrity of the work.

Conflict 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 supporting the findings of this study are available upon reasonable request. Access to interview transcripts or research materials may be granted for scholarly and non-commercial use.

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Discord Connects: Fostering Social Presence in Higher Education

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Abstract
Student engagement in online and blended learning environments depends on fostering social presence, yet institutional communication tools can fail to support the informal and dynamic interactions that build a sense of community. While Learning Management System discussion boards provide structured communication, students increasingly turn to external platforms such as Discord, which can offer more effective opportunities for collaboration and engagement. Despite growing interest in student-led communication tools, research comparing their effectiveness with institutional platforms remains limited. This study examines the role of Discord in fostering social presence in a first-year university game design course over six years, comparing its use from 2018 to 2022 with Canvas Discussions in 2023. A longitudinal case study including content analysis of over 1300 online interactions was conducted to investigate student engagement and the presence of social indicators across both platforms, with illustrative examples included to demonstrate how these indicators manifested in practice. Findings indicated that students posted more frequently and demonstrated significantly higher indicators of social presence when using Discord, whereas student posts on Learning Management System discussion boards showed limited to no indicators of social presence. The analysis also revealed how the nature of social presence shifted over time, shaped by platform features and influenced by external factors such as the COVID-19 pandemic. These results suggest that informal, student-oriented communication platforms may be more effective than institutionally controlled Learning Management System discussion boards in promoting interaction and community building in online learning. The study contributes to discussions on digital pedagogy by highlighting the role of platform selection in shaping student engagement and social presence in higher education.

Keywords: Social presence, Community of Inquiry, Discord, Canvas, longitudinal case study, blended learning.

Stieler-Hunt, C., Marshman, M., Elsom, S., Bennett, J., Muscat, A., & Hargraves, C. (2026). Discord connects: Fostering social presence in higher education. *Online Learning, 30*(3), 532-560. https://doi.org/10.24059/olj.v30i3.4974

Student engagement in online and blended learning environments depends on fostering social presence, yet in our experience, institutional communication tools often fail to support the informal and dynamic interactions that build a sense of community. While Learning Management System (LMS) discussion boards provide structured communication, students within our institutional context increasingly turn to external platforms such as Discord, which can offer more effective opportunities for collaboration and engagement. Our interest in the online community platform Discord as a medium for student discussion was piqued by research carried out separately by members of our research team, which consists of teaching and research staff associated with the course over the period of the study. For several years, our university's introductory game design course *SGD100* had an embedded Alternate Reality Game (ARG) in its curriculum and game-based learning researchers investigated the course to determine the impact of the game on engagement and learning. Though Discord was not the original focus of these studies, student feedback and observations highlighted its role in supporting participation, which spurred our interest in examining the platform's potential to impact social interaction in the course.

To further understand the potential of Discord as a driver of social participation in learning, we conducted a six academic year longitudinal quantitative study. The Community of Inquiry framework (Garrison, Anderson, & Archer, 1999) is widely used in studies exploring online and blended learning contexts (for example, Martin et al., 2022; Meech & Koehler, 2024) for analysing written transcripts. While the framework encompasses three presences (social, teaching, and cognitive) necessary for a full educational experience, we focused on social presence to limit the scope of the study and address our primary interest in learning how communication platforms affect social interactions in higher education. Garrison describes social presence as "the ability to project oneself and establish personal and purposeful relationships" (2007, p.63).

Online community platforms are an important component of online and blended learning. We explored Discord as a digital platform and its evolution in higher education from a student backchannel to a more central communication tool, particularly during the COVID-19 pandemic and compared students' use of Discord with the Canvas LMS Discussion Boards. Our aim was to determine how Discord impacted social presence in the multiple iterations of this course. We hypothesised that Discord would be found to be a tool that was engaging students and increasing social presence in a post-pandemic world. Our findings suggest that informal, student-oriented communication platforms such as Discord may be more effective than institutionally controlled LMS discussion boards at promoting student interaction and building an online community of learning.

In recent years, informal communication platforms have become increasingly prominent in higher education, driven by their capacity to facilitate peer-to-peer interaction, foster a sense of belonging, and support collaborative learning beyond formal class time (Kahu, Thomas, & Heinrich, 2024; Vladoiu & Constantinescu, 2020). Tools such as Discord, WhatsApp, and Slack allow students to create dynamic, student-led spaces that complement formal learning management systems by enabling real-time, multimodal, and socially rich interactions (Fiester & Green, 2016; Harunasari & Halim, 2019). However, their integration into educational contexts presents several challenges. First, because these platforms operate outside institutional systems, they raise concerns about oversight, data privacy, and alignment with university policies (Crookes, 2019; Kahu et al., 2024). Second, effective participation often requires a degree of prior familiarity with platform conventions, which can disadvantage students with less digital literacy or experience (Rinekso &

Muslim, 2020). These opportunities and risks underline the importance of understanding how informal platforms can be purposefully leveraged to enhance social presence while maintaining accessibility, equity, and institutional safeguards.

Literature Review

The importance of social interaction for learning in higher education has been widely recognised, but replicating the classroom sense of community can be challenging in online learning situations. One influential model for understanding online and blended learning is the Community of Inquiry (CoI) framework, developed by Garrison, Anderson, and Archer (1999). This framework proposed that effective online learning occurs through the interaction of three core elements: cognitive presence, teaching presence, and social presence. Cognitive presence refers to the extent to which learners are able to construct and confirm meaning through sustained reflection and discourse. Teaching presence involves the design, facilitation, and direction of cognitive and social processes to achieve meaningful learning outcomes. Social presence, the focus of this study, is defined as the ability of participants to identify with the community, communicate purposefully, and develop interpersonal relationships by projecting their personal characteristics into the online environment (Garrison, 2007). Social presence is particularly crucial in online learning because it can help reduce feelings of isolation, foster peer interaction, and contribute to overall engagement and satisfaction.

Armellini and De Stefani (2016) argued that social presence plays an increasingly central role in online education, especially as informal and community-based platforms gain popularity. They contended that social presence not only facilitated interaction but also acts as a mediator that enhanced both cognitive and teaching presence. Similarly, Bentley, Secret, and Cummings (2015) highlighted the centrality of social presence in fostering authentic communication and building a sense of community in online learning, particularly in disciplines that rely on interpersonal connection. In this sense, supporting social presence is not merely a matter of increasing student comfort, it has implications for deeper engagement with content and more effective teaching practices. Building on this recognition of social presence as a core element of online learning, other researchers have proposed extensions to the CoI model to capture more nuanced dimensions of social presence. Whiteside (2015) introduced the Social Presence Model (SPM), which included emotional expression, interaction intensity, and instructor involvement as key components of online engagement. SPM builds on CoI by highlighting how affective tone and informal discourse contributed to the formation of connected learning communities.

The value of these theoretical contributions is further supported by large-scale empirical evidence. A meta-analysis by Richardson, Maeda, and Swan (2017) found that social presence had a significant positive effect on both student satisfaction and perceived learning in online environments. Similarly, Martin, Wu, Wan, and Xie (2022) analysed over a hundred studies using the CoI model and concluded that social presence consistently correlates with favourable learning outcomes in both online and blended learning contexts. These findings reinforced the importance of understanding how social presence is shaped by different communication tools and environments. Tu and McIsaac (2002) provided early empirical evidence that social presence strongly correlated with interaction frequency and satisfaction in online learning. Their work highlighted that social presence is not merely a social construct but a significant determinant of learner participation and retention. Kehrwald (2008) further argued that in text-based online environments, social presence is

often inferred through subtle cues such as timing, tone, and narrative style rather than explicit statements.

Online and blended learning in higher education have grown considerably since the COVID-19 pandemic-induced lockdowns. This underscores the need to develop new methods of communication that help students to feel part of a community of learners, to make connections and develop a sense of belonging like what they would experience in a traditional classroom setting. Discord launched in 2015, primarily as a tool for gamers. With 154 million active monthly users as of January 2023 (Ceci, 2024), Discord is one of the platforms that has emerged as a significant tool that may be used to support learning. Kruglyk et al. (2020) examined the use of Discord as an online learning environment during the pandemic and found that nearly 80% of students were in favour of using Discord for learning. The study described Discord as low-cost, flexible, and convenient. It placed minimal load on the user's computer or internet. It supported multimodal communication (text, images, audio), and it allowed both group and private conversations. Importantly, it could be customised by instructors to suit their pedagogical needs. Constantinescu (2020) reported that Discord helped students communicate with peers and alumni, enhancing their integration into the learning environment. These studies point toward Discord's potential to foster social presence, particularly in the affective and cohesive indicators within the social presence dimension of the CoI framework, through informal tone, peer support, and flexible interaction patterns.

Ghazali (2021) applied the CoI framework directly to the design of Discord-based classes during the pandemic, aiming to overcome the isolation students experienced in lockdowns. While initial attempts used Google Meet and WhatsApp, a lack of social presence was identified. Ghazali replaced these with Discord, creating activities tailored to each CoI element. For example, students were randomly placed in voice channels to promote peer interaction and social presence. Students reported that the platform made classes feel more relaxed, fun, and motivating due to the presence of peers. This example illustrates how deliberate instructional design using informal tools like Discord can support social, cognitive, and teaching presence. While Ghazali transitioned to Discord, Rinekso and Muslim (2020) reported positive outcomes using WhatsApp, a platform already familiar to students. Most discussion in their study was facilitated by students themselves, highlighting how existing student digital habits influence engagement and presence. This aligns with the CoI model's emphasis on learner autonomy and the centrality of perceived relevance in fostering meaningful engagement. In our own context, Discord was selected not only for its communication affordances but also because it is widely used in the game development industry and already familiar to many students, allowing us to leverage their existing communication practices to support engagement.

After the period of emergency remote learning (Hodges et al., 2020), Banson and Hardin (2022) examined how the use of Discord impacted students' academic performance and ability to connect with their classmates. They found that students had positive experiences with Discord and perceived it as a helpful communication tool that helped them to feel a sense of belonging in the class. The students appreciated the ease of use, quick response times, and social aspect of Discord, evidenced by 75% of students reporting that they were highly comfortable with Discord and 20% of students using the class Discord platform at least daily. These outcomes suggest strong interactional and affective presence, reinforcing the value of Discord in informal learning communities.

Unlike formal communication tools embedded in LMSs such as Canvas Discussions, Discord is one of many tools that can act as a student backchannel. Backchannels are digital platforms that enable secondary, digital conversations to occur alongside primary educational activities, enhancing student engagement and participation (Fiester & Green, 2016). In contrast to a front channel which is the primary method of communication in a learning space, backchannels facilitate parallel online discussions that complement traditional classroom interactions. They offer a space for students to ask questions, express opinions, and provide feedback without the fear of embarrassment, promoting a more inclusive learning environment (Harunasari & Halim, 2019).

The technologies used for student backchannels have varied and along with Discord include TodaysMeet, Backchannel Chat, GoSoapBox, Mentimeter, Pear Deck (Harunasari & Halim, 2019), Padlet, Skype, Google Hangouts, and chat features in video conferencing tools like Zoom (Fiester & Green, 2016). Prior to the pandemic, backchannels were primarily used to break the passivity of traditional lecture formats, encouraging active student engagement (Baron et al., 2015). These platforms addressed challenges posed by large class sizes and diverse student needs, providing a medium through which students could engage with content and peers. The adoption of backchannels in higher education has been positive, with studies showing that they significantly increase participation among students, and provide immediate feedback to lecturers, thereby enhancing the overall learning experience (Kassner & Cassada, 2017).

However, there are potential downsides to the use of Discord in a formal education setting. Crookes (2019) points out that the platform has been associated with criminal activities and criticised for the sharing of non-consensual pornography and violent imagery. Despite the positive response to Discord in Banson and Hardin's (2022) study, the researchers also noted that students lost interest in reading the Discord when it was overwhelmed with irrelevant comments, and that the use of Discord for non-class related activities was distracting for some students. These findings speak to a tension within the CoI framework: While informality may promote social presence, a lack of teaching presence or moderation may undermine learning goals. Therefore, educators must weigh the benefits of informality with the need for structured facilitation.

More recently, Kahu et al. (2024) considered the potential of Discord as a learning support in higher education. In response to the shift towards digital communication platforms during COVID-19, the researchers proposed the formalisation of informal backchannels into Learning Commons Communication Tools. These tools could offer structured support, improved accessibility, and consistent application across educational settings. However, Kahu and colleagues stress that formalisation should not erode the flexibility that makes these platforms effective. The challenge is to balance institutional oversight with the peer-led, community-oriented affordances that promote social presence in student-driven platforms.

While the literature confirms Discord's value in fostering student engagement, it rarely addresses how the platform's features map onto CoI's full spectrum of social presence indicators, or how these indicators compare longitudinally with institutional tools like Canvas. Furthermore, few studies have examined platform use across multiple learning conditions over time. This study addresses that gap by investigating how Discord, as a student-preferred platform, influenced social presence in a first-year game design course. The central research question guiding this study is:

How has the use of a popular server-based chat communication platform, Discord, impacted social presence in multiple iterations of a blended learning course?

This question was supplemented with the following sub-questions:

In what ways did the use of Discord impact social presence over the years 2018-2022?

How was social presence impacted using Discord compared with the use of the Learning Management System (Canvas Discussions) in 2023?

Context

This research focused on the course, *SGD100 Introduction to Game Design* that used Discord as an informal communication platform and backchannel for students between 2018-2022, examining its use before, during, and after the pandemic. The course was a 12-credit point (one quarter of a full-time load) first-year game design course for students interested in becoming game designers and developers. The course took place over a 13-week teaching semester with an additional two weeks for assessment. The course is part of a Bachelor of Design degree at a regional Australian university with a student population of 12 450 in March 2022 ([institution redacted], 2023) Studies in game development attract and nurture a significant number of students who have disabilities as well as young male students (currently underrepresented in this University's cohort, which in 2020 was 68% female). Students with disabilities are more highly represented in the game design cohort at nearly 18% (compared to 6.5% in the general university population); the game design cohort tends to be predominantly young, male, and full-time (USCBI data cited in Stieler-Hunt, Hargraves, & Elsom, 2021).

The course was initially delivered face-to-face but shifted to blended and online formats during the pandemic. In 2023, the course transitioned to the institution's LMS Discussion Boards, providing a point of comparison between a student-driven external platform and a formal, institutionally controlled tool. This timeline provided a natural opportunity to explore how Discord shaped social presence under varied learning conditions, ranging from pre-pandemic face-to-face delivery to post-pandemic blended and online adaptations. Examining these shifts allowed us to consider not only how students used the platform, but also how different teaching contexts may have influenced their engagement.

To understand how Discord functioned in practice, it is also important to describe how the servers were set up and managed across different years. In 2018 and 2019, *SGD100* shared a Discord server accessible by all students in the Game Design program at our university. We thought that having a shared server would encourage a sense of belonging for the entire game design cohort starting from first year through to the final year students. However, it became difficult for staff to manage as it was unclear precisely which staff members were responsible for which parts of the server. The shared server also had "bots" which were designed to moderate profanity and check language for inclusivity, as well as a "levelling up" system. At the end of 2019 we shut down the shared server due to a conflict that occurred in one of the common areas of the server. From 2020–2022, the course coordinator for *SGD100* created a new "server" for each course cohort. Bots were not used in these servers. This enabled the course coordinator to know exactly who was in the server

and made it easier to identify anyone not meant to be there. It was also clear who was responsible for conduct, and what was determined to be acceptable conduct, inside the server. The downside of this was that there was less fraternising between students in other years and students who were further along in their studies could not take on an informal role of helping other students.

To maintain clarity and accountability on each server, the coordinator required students to change their nickname to match their university records, with any unrecognised names removed. Communication was intentionally limited to text-based channels, rather than audio or video, so that every interaction could be reviewed if needed and inappropriate behaviour could be addressed transparently. Alongside these spaces, a dedicated "rules" channel set out the expectations for participation. Here, students were reminded to use their real names, approach the space as a professional environment, and interact with kindness and inclusivity. The channel also linked directly to the university's student code of conduct and presented 15 rules of netiquette, reinforcing shared standards of online behaviour. These guidelines not only clarified what would happen if a student made an inappropriate comment but also framed Discord as an extension of the classroom, a professional yet supportive community space.

The Course Coordinators had Discord on their computer, phone, and tablet and received notifications in real time as students posted. If a post was inappropriate, depending on the severity, the course coordinator would:

- Send the student a private message asking them to edit or remove the post.
- Remove the post immediately and communicate with the student.
- Remove the student from the server immediately for severely inappropriate posts.

To date, we have never had to remove a student from the server and there are very few inappropriate posts made; usually some non-inclusive language is flagged in the early parts of the semester.

From 2018–2021 we were running an alternate reality game (ARG), *Against The Authority* (Stieler-Hunt, Hargraves & Elsom, 2021; Hargraves, 2023), within the class and, at different times, we had two researchers exploring the impacts of that game on the students. The game is not the focus of this study. However, we acknowledge that the game may have driven some of the traffic on the server. The ARG involved the researcher or the course coordinator posting to the server as fictitious game characters. These posts were often giving students feedback on game design concepts or their game designs. This research treats game character posts as tutor posts. The iterations of the course were:

- 2018–2019: Traditional delivery (face-to-face) with ARG and Discord.
- 2020–2021: Hybrid delivery (face to face and online due to COVID-19 lockdowns), continuing both ARG and Discord.
- 2022: Traditional and online delivery with Discord and without the ARG.
- 2023: Traditional and online delivery with Canvas LMS Discussion Boards instead of Discord and without the ARG.

Methodology and Methods

Research Design and Approach

This longitudinal case study analyses social presence in an online learning environment using content analysis. A case study approach is an empirical inquiry that investigates a phenomenon within its real-life context, especially when the boundaries between phenomenon and context are not clear (Cohen et al., 2018, Yin, 2018). Whilst case study may not be representative, the data is "illustrative and illuminating, … strong in reality [and] … recognize[s] the complexity and 'embeddedness' of social truths" (Cohen et al., 2018, pp.378–379). The case is the communication platform in *SGD100 Introduction to Game Design.* Hence, case study was well suited to this research because the boundaries between the communication platform and the learning environment were not clear-cut and the complexity was acknowledged. This design allowed for a detailed investigation of social presence dynamics within a specific educational setting, while illustrative examples are included to demonstrate how indicators of social presence were coded in context. The study provides a comprehensive examination of student engagement in a serious game design course, *Introduction to Game Design (SGD100)* at [Institution Redacted] over six years (2018–2023).

A content analysis design (Cohen et al., 2018; Maier, 2017; Miles et al., 2014) allowed for a nuanced exploration of how social presence evolved as the course transitioned between in-person and online formats across different communication platforms. Initially, the course relied on Discord as the primary communication tool, chosen for its popularity within the gaming community and its relevance to professional practices in game design. However, in 2023, Discord was replaced by Canvas Discussions, enabling a natural comparison of the platforms' effectiveness in supporting social presence. By tracking and analysing these transitions, the study observes how the shift to an online-centred delivery has influenced the nature and frequency of social presence behaviours among students.

Conceptual Framework

This study applied the Community of Inquiry (CoI) framework (Garrison, Anderson, & Archer, 1999) as an analytic lens with a focus on social presence, as outlined in the Literature Review. To operationalise this construct, we used Rourke et al.'s (1999) coding scheme, which categorises social presence indicators as affective, interactive, or cohesive. These categories capture emotional expression and self-disclosure (affective), reciprocal communication such as questions or acknowledgements (interactive), and markers of group belonging such as greetings and inclusive pronouns (cohesive). Together, they provide a structured way to compare how Discord and Canvas supported the development of community through student interactions. Later refinements to the social presence indicators (Aykol & Garrison, 2019) using learning climate and risk-free expression were not applied as the available data did not support such analysis.

Methods

Ethics approval was received from the University of the Sunshine Coast Human Research Ethics Committee (approval number A231918). This study analysed text-based course communications for evidence of social presence over a six-year period in the delivery of the undergraduate course SGD100: Introduction to Game Design at the University of the Sunshine Coast. From 2018 to 2022, students used the Discord platform for informal course communication and community building, while in 2023 the course transitioned to using the Canvas Discussions tool exclusively. The study was designed post

hoc and emerged from earlier independent investigations by two researchers into the use of an alternate reality game (ARG) embedded within the course (Stieler-Hunt, Hargraves & Elsom, 2021; Hargraves, 2023). During these investigations, one researcher noted that student interviews highlighted Discord as a positive contributor to their learning experience and sense of connection. These quotes from interviews with student research participants demonstrate this:

- I find that if it's just Zoom, then it's like this call, it's like a class you just rock up to, but Discord ties that together where people are talking, and the team can still chat outside of actual calls.
- It was good to continue conversations that otherwise, you know… you would only see people for three hours a week and then you won't be able to talk to them until the next time and you'd forget everything.
- I was very comfortable with Discord. It's my main social media platform I use.

To understand further, the research team initiated a retrospective analysis of student communications to explore the potential role of Discord in supporting social presence. The decision to focus on social presence was informed by its status as a well-established predictor of student engagement, satisfaction, and persistence in online and blended learning environments. By centering on social presence, we aimed to investigate how platform choice shapes students' capacity to form meaningful connections and sustain engagement in higher education.

As outlined in the Conceptual Framework, we drew on the coding scheme established by Rourke et al. (1999). Table 1 presents the three categories of social presence (affective, interactive, and cohesive) alongside their indicators and examples, with verbatim excerpts from our dataset illustrating how these categories were operationalised. Weeks 2 and 6 of each semester were selected to maximise relevance and data continuity, following Rourke et al. (1999), who similarly used discrete weeks of data as indicative of broader conversation patterns. Week 2 generally captures high levels of student engagement as course activities commence, while week 6 reflects a more stable stage of participation once group dynamics have formed and is less affected by external disruptions. This sampling strategy allowed us to compare interaction patterns across platforms and cohorts while maintaining consistency.

Table 1

How We Used Rourke and Colleagues (1999) Social Presence Categories and Indicators

Category	Indicators	Examples from Rourke	Examples from this study (verbatim)
Affective	Expression of emotion*	"I just can't stand it when… !!!!" "ANYBODY OUT THERE!"	"Yes <name> lol" "Will give it a go!! Thanks a bunch"

	Use of humour	"The banana crop in Edmonton is looking good this year"	In reply to a student asking for how to self-treat insomnia: "throw your phone out the window (accompanied by a funny image)"
	Self-disclosure	"Where I work, this is what we do…" "I just don't understand the question"	"im not too sure if this is correct. Litteraly basing my experience of baseball on wii sports"
Interactive	Continuing a thread*	Software dependent e.g. "Subject: Re" "Branch from	In reply to a message about where something is located, "<student tagged> It should be at D block, or more specifically room DG.40" Exchange between two students (the second two messages in this exchange are examples of replies): Student 1: "you think it'd be worthwhile making a google docs we can all chip into?" Student 2: "'ll make one now" Student 1: "Cheers"
	Quoting from other messages*	Software dependent e.g. "Martha writes:" Or text prefaced by less-than symbol <.	
	Referring to explicitly to others' messages*	"In your message you talked about Moore's distinction between…"	
	Asking questions	"Anyone else had experience with WEBCT?"	"for Video 1- does anyone think it sounds like she's describing a game?"
	Complimenting, expressing appreciation	"I really like your interpretation of the reading."	"again, thank you so much" "you've saved me a trip to the ER"

	Expressing agreement	"I was thinking the same thing. You really hit the nail on the head."	"Yea, now that i'm reading my response I can see how I would have described the game in too much detail. The quote you pulled from the interview I posted seems like a more reasonable and adequate pxg."
Cohesive	Vocatives*	"I think John made a good point." "John, what do you think?"	"<Student name> there is a doc that gives you a list of serious games. I think it means that games that doesn't just do entertainment e.g. Pokemon Go while it was a game it got people moving around."
	Address or refers to the group using inclusive pronouns	"Our textbook refers to…" "I think we veered off track…"	"Hi, I'm still sorting out responding to the latest news and the ice breaker game we made"
	Phatics, salutations	"Hi all" "That's it for now" "We're having the most beautiful weather here"	Tutor: "Thanks for kicking us off <Name>. Nice observations!"

Messages were exported from Discord using Discord Chat Exporter (hypercavs, 2022) extension for Chrome web browser, while Canvas posts were manually compiled. Coding of these messages was undertaken in Excel with one spreadsheet for each year. Each message was coded into one or more of the three social presence categories (affective, interactive, or cohesive) if it demonstrated relevant indicators, allowing for multiple classifications within a single message where applicable. Coding at the category rather than indicator level provided a consistent basis for comparison across platforms.

Two coders independently read the full content of each message and made a binary judgment ("yes" or "no") as to whether it demonstrated one or more of the three categories. A "notes" column was used to record uncertainties and highlight which indicators seemed most relevant, although indicators themselves were not formally coded. Inter-rater reliability was assessed through initial double-coding, which demonstrated a high level of agreement. Discrepancies were resolved through discussion in research meetings until consensus was reached, following established practices for content analysis. To support consistency, the research team also established shared clarifications for how the categories would be applied in practice:

- **Affective – Expression of Emotion:**
  Exclamation marks and other emphatic punctuation were interpreted as emotional expression. Posts were also coded as affective when emotions were directly named (e.g., "annoyed," "fun")

- **Interactive – Continuing a Thread, Quoting from Other Messages, Referring Explicitly to Others' Messages:**
  Indicators such as continuing a thread, quoting messages, or explicitly referring to others' posts were treated collectively, as they often overlapped and were difficult to distinguish reliably. Because the Discord export did not retain reply to metadata, coders inferred interactivity from textual and contextual cues (e.g., direct references to earlier messages).

- **Cohesive – Vocatives:**
  Posts were coded as cohesive when participants were addressed directly by name. In some cases, contextual interpretation was required to determine whether a reference was directed at a specific individual.

Across the six years, a total of 1,339 posts were coded. The dataset included four years (2018–2021) of Discord use in combination with an interactive ARG activity, one year (2022) of Discord use without the ARG, and one year (2023) of Canvas use without the ARG. In contrast to Discord, where students could freely initiate conversations, Canvas Discussions were structured around instructor-created threads. Students participated by replying to these posts rather than starting new discussions themselves, which may have influenced both the volume of posts and the types of social presence indicators observed. Table 2 summarises the participants and posting activity across these iterations.

Table 2

Summary of Participants and Data Collected

Year	Student communication platform	Interactive ARG included?	Number of students in cohort	Number of tutors	Number of posts in Weeks 2 & 6
2018	Discord	Yes	17	1	45
2019	Discord	Yes	41	1	347
2020	Discord	Yes	37	1	147
2021	Discord	Yes	75	3	554
2022	Discord	No	71	2	218
2023	Canvas	No	22	2	28

The primary data source for this study was student and teaching staff communication via Discord and Canvas Discussion Board. Interview data from separate

studies are used selectively to illustrate and contextualise these findings but were not part of the dataset for analysis. Validity of the content analysis was achieved with at least two of the research team analysing each online post and differences resolved with team discussion (Cohen et al., 2018; O'Leary, 2017). Reliability was achieved through research team discussions to ensure close adherence to the theoretical framework (Miles et al., 2014; O'Leary, 2017). The necessity to infer meaning (Yin, 2018) from online posts is potentially a limitation of this study.

Results

After coding the contents of each of the SGD100 posts from weeks 2 and 6 for the years 2018 to 2023, the data was collated and analysed to identify trends. The analysis began with examining the number of posts made each year, followed by assessing how many of those posts demonstrated social presence, and concluding with an exploration of the most dominant categories of social presence.

Number of Posts

Table 3 presents, for each year, the platform used, the cohort size, the number of tutors, and detailed posting activity during weeks 2 and 6. This includes the total and mean number of posts by students and tutors, the number of unique students who posted, and the maximum posts made by an individual student.

Table 3

Messages Posted by Students and Tutors in Weeks 2 and 6 for SGD100 Between 2018 And 2023

	Year	2018	2019	2020	2021	2022	2023
	Platform Used	Discord	Discord	Discord	Discord	Discord	Canvas
	Number of Students in Cohort	17	41	37	75	71	22
	Number of Tutors	1	1	1	3	3	2
Weeks 2 & 6	Number of Student Posts	20 47.62%	216 65.85%	69 46.94%	446 80.51%	192 88.07%	9 32.14%
	Number of Tutor Posts	22 52.38%	112 34.15%	78 53.06%	108 19.49%	26 11.93%	19 67.86%
	Mean Number of Posts per Student	1.18	5.27	1.86	5.95	2.70	0.41
	Mean Number of Posts per Tutor	22.00	112.00	78.00	36.00	8.67	9.50

Number of Students Posting	4 23.53%	28 68.29%	11 29.73%*	38 50.67%*	33 46.48%	7 31.82%
Number of Students not Posting	13 76.47%	13 31.71%	26 70.27%	37 49.33%	38 53.52%	15 68.18%
Maximum number of posts by an individual student	15 75.00%	52 24.07%	19 27.54%	123 27.58%	31 16.15%	2 22.22%

* *At the time of download some students had left the server and were now identified as DeletedUser. It is unknown how many students DeletedUser represents. For the purposes of this analysis, these have been listed as one user.*

Comparing the Use of Canvas with Discord

Before turning to coded data, it is useful to note key functional differences between Discord and Canvas. These affordances shaped how students interacted and may help explain the variation in social presence across platforms. Table 4 summarises these features.

Table 4

Comparing Features Offered by Discord with Canvas Discussions

Feature	Discord	Canvas Discussions
Real-time Communication	Yes, supports real-time text, voice, and video chat.	No, discussions happen asynchronously via posts and replies.
Threaded Discussions	Yes, supports threads to organise conversations within channels, but can get chaotic in large groups.	Yes, discussions are neatly threaded under posts for organised conversations.
Multimedia Support	Yes, supports embedding of media and links within posts.	Yes, supports embedding of media and links within posts.
Emoji, Stickers and GIF Support	Yes, natively supported and custom support is available through paid services.	No
Voice & Video Integration	Yes, built-in voice and video chat for instant communication.	No
Notifications	Yes, customisable notifications for specific channels or servers.	Yes, but it is platform-wide, not customisable by specific posts.
File Sharing	Yes, but with limitations based on server settings.	Yes

Roles & Permissions	Custom roles and permissions can be assigned per server/channel.	Limited to standard student and instructor roles with access permissions.
Search Functionality	Yes, but lacks organisation in large channels.	Yes, but it is easier to search by topic.
Privacy	Yes, but user data is collected by Discord.	Yes, typically within a secure, academic environment.
Mobile & Desktop Access	Yes, available via mobile and desktop apps.	Yes, available via mobile and desktop browsers, but there is no dedicated app for discussions.
Learning Analytics	No	Yes, tracks participation and engagement through the Canvas LMS.
Integration with Other Tools	Yes, it easily integrates with other tools via bots, webhooks, etc.	Limited, integrates with Canvas's suite of educational tools, but more restricted.
Access Control	Highly customisable access to different channels based on roles.	Access is usually limited to the course and assigned by the instructor.
Moderation Tools	Advanced moderation features with bots and manual controls.	Limited moderation features, managed by the instructor.
User Community	Highly active and engaging, especially for casual or community-based interaction.	Focused on academic discussion with formal and structured participation.
Anonymity	Users can choose their display names and remain somewhat anonymous.	Linked to the student's institutional profile, offering no anonymity.
Collaboration Features	Supports screen sharing, live streaming, and other collaborative tools.	Primarily text-based discussion with limited real-time collaboration.
Data Storage/Archiving	Messages stored indefinitely unless deleted.	Discussions are archived within the course, easily accessed for academic purposes.
Customisation	Highly customisable with bots, emojis, and themes for each server.	Limited customisation, with standard formatting for posts.

Onboarding and Learning Curve	Can have a steeper learning curve for users unfamiliar with its layout.	Low learning curve, straightforward, and integrated into the LMS.

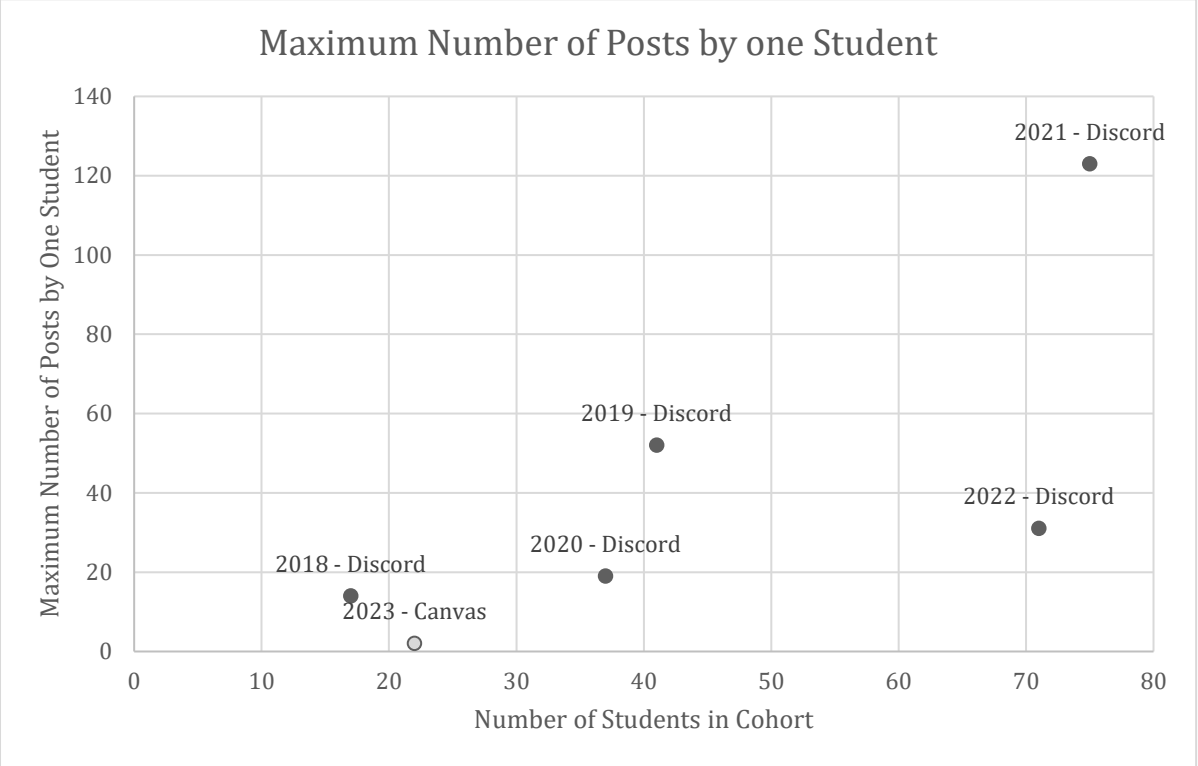
As indicated in Table 3, in 2018 – 2022 when Discord was used, the mean number of student posts (ranging from 1.18 – 5.95 posts per student) was greater than the mean number of student posts (0.41) in 2023 when Canvas Discussions was used. The increase in the mean number of student posts could have been caused by a "network effect" where more people create more posts, generating more opportunities for responses (Swann 2002). Therefore, the use of Discord in 2018 (student enrolments = 17) was compared with the use of Canvas in 2023 (student enrolments = 22). Given that Discord has grown in popularity since 2018 and the slightly smaller number of enrolments in 2018, this comparison would give the 2023 Canvas Discussions an advantage. However, the mean number of posts per student (1.18) when using Discord in 2018 was still higher than when using Canvas Discussions in 2023 (0.41). Therefore, based on this limited data set, it appears that there will be more posts from students when Discord is used rather than Canvas Discussions. Excluding 2020 (when there was a move to emergency remote learning) the percentage of students who posted grew each year in Discord. When Canvas was the collaboration tool 30.43% of enrolled students posted whilst in Discord it varied between 23.53% and 68.29% of students who posted.

Domination by a Single Student

In 2018 the Discord server seemed to be dominated by one student. Three-quarters of student posts (15 posts) in weeks 2 and 6 in 2018, were made by one student (See Table 4). This level of domination did not occur in other years with the most posts from one student ranging from 16.15% (31 posts) in 2022 and 27.58% (123 posts) in 2021, even though the actual number of posts by an individual student increased from 18 in 2018 to 123 in 2021. There also appeared to be a network effect (Swann, 2002) in the data; in four of the five years that used Discord, the maximum number of posts by one student was higher when the student population was higher (see figure 2). The exception to this was 2022, and it may have been due to a change in teaching staff or that the ARG used in the classroom was discontinued.

Figure 2

Maximum Number of Posts by One Student



In 2023, student participation in Canvas Discussions was limited, with the highest number of posts by a single student being two (see Table 4). Other indicators also suggest lower levels of engagement on this platform. One possible explanation is the absence of instant notifications, a feature available on Discord that facilitates real-time conversations. Without this functionality, interactions on Canvas may have been less dynamic and immediate.

Pandemic Effect

In south-east Queensland, 2020 was the year most disrupted by the COVID-19 pandemic; classes were converted to emergency remote learning. Table 4 shows that in 2020 there was a lower number of mean posts per student than the other years that used Discord, except 2018 which is when Discord was first introduced. However, 2020 still had more mean posts per student than when Canvas was used in 2023. Further, in 2020 the tutor was responsible for 53.06% of posts (students were responsible for 46.94% of posts), which is greater than the percentages for 2019, 2021 and 2022 when the percentage of posts by tutors ranged from 11.93% to 34.15%. This may indicate that when students are in distress, their studies will become less important than their personal situation; and despite being a useful tool, Discord is not a "silver bullet" that can "fix" all student engagement issues.

Posts Coded as Demonstrating Social Presence

In Discord, most student post content was coded as demonstrating one or more categories of social presence. In 2018, 60% of student posts demonstrated one or more categories of social presence, whilst from 2019-2022 the percentage of student posts demonstrating one or more categories of social presence varied between 84.06% and 97.53%. Even in 2020, during the pandemic, when the number of posts was considerably

lower, 84.06% of student posts still demonstrated a social presence (See Table 5). However, in 2023, when the collaboration tool was changed to Canvas, none of the student post content was coded as demonstrating social presence. One possible explanation is that students perceived Canvas as a formal, institutionally controlled platform rather than a social medium, in contrast to Discord, which they associated with informal peer interaction.

Figure 3a–f shows the distribution of posts coded for social presence by individual students between 2018 and 2023. Generally, most students either made no posts or made a small number of posts (between one and ten) with content demonstrating social presence in weeks 2 and 6. In 2019 there was one student who made 51 posts with social presence and in 2021 there were three students who dominated the posts: one student made 60 posts demonstrating social presence, one 105, and one student made 121 posts demonstrating social presence. (Note that the 105 posts demonstrating social presence were made by DeletedUser. The course coordinator believed that may have been only one student as she was very aware that year that one student who regularly maintained their presence on Discord dominated the posts. There may, however, have been more than one student who deleted their username.)

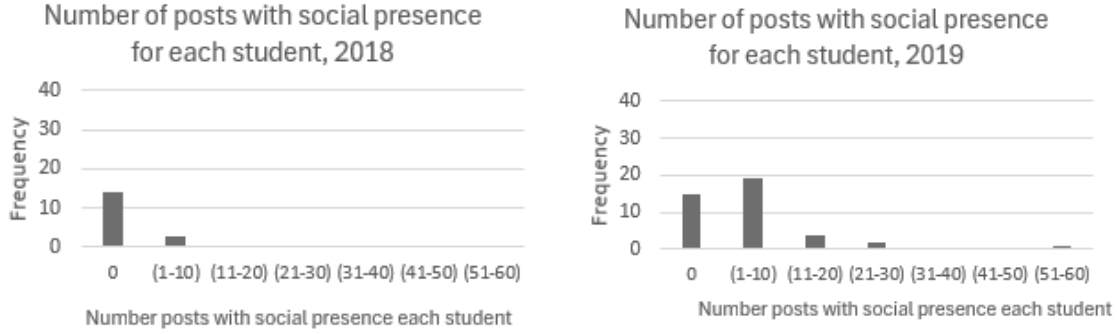
Table 5

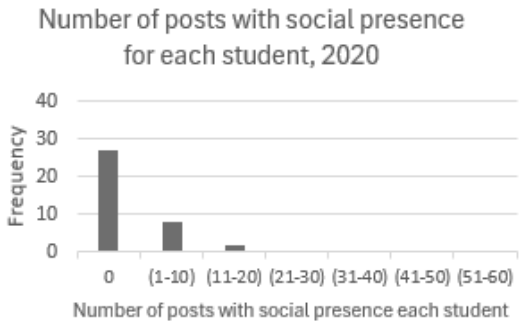
Number of Students with No Posts Coded as Demonstrating Social Presence

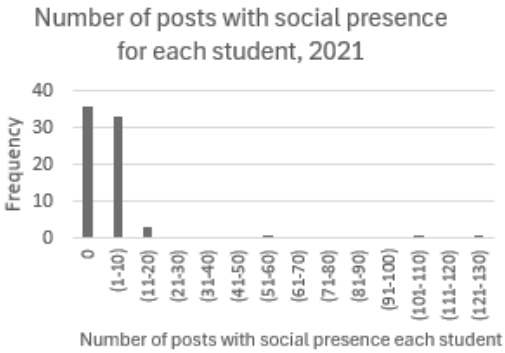
	2018	2019	2020	2021	2022	2023
Number of students who did not upload a post with social presence	14 82.35%	15 36.59%	27 72.97%	36 48.00%	39 54.93%	22 100%
Number of students who did not post	13 76.47%	13 31.71%	26 70.27%	37 49.33%	38 53.52%	15 68.18%
Number of students in cohort	17	41	37	75	71	22
Number of student posts	20	216	69	446	192	9
Number of student posts with social presence	12 60.00%	210 97.22%	58 84.06%	435 97.53%	188 97.92%	0 0%

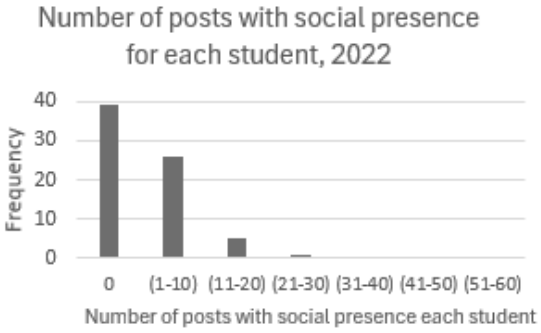
Figure 3a-f

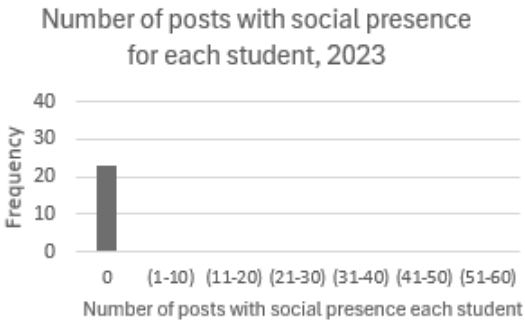
Number of Posts with Social Presence Made by Each Individual Student for Each of the Years 2018 to 2023











As shown in Table 6, all years that used Discord showed that student posts were more likely to be coded as demonstrating social presence. In 2018, 60% of posts were coded as demonstrating at least one social presence category whilst in all subsequent years, except the year most affected by the pandemic, more than 97% of student posts were coded as demonstrating social presence. In 2020, the year most affected by the pandemic, this dropped to 84.06%, which is still reasonably high. In stark contrast, in 2023 when Canvas Discussions was used, no student posts were coded as demonstrating social presence.

Table 6

Student Posts Coded as Demonstrating Social Presence, Maximum Posts Coded Per Individual Student, and Mean Number of Posts Coded Per Student

Year	2018	2019	2020	2021	2022	2023
Number of student posts coded as demonstrating social presence	12 60.00%	210 97.22%	58 84.06%	435 97.53%	188 97.92%	0 0.00%
Number of student posts not coded as demonstrating social presence	8 40.00%	6 2.78%	9 13.43%	10 2.23%	4 2.08%	9 100%
Maximum number of posts coded as demonstrating social presence by an individual student	9	52	16	121	29	0

Mean number of posts coded as demonstrating social presence per student	0.71	5.12	1.57	5.80	2.65	0
SD	0.815	2.235	1.235	2.392	1.616	0
Number of students	17	41	37	75	71	22

Considering Student Social Presence Posts with t-Tests

To determine whether there were significant differences between the mean number of posts per student each year t-tests were conducted. Table 7 shows that the mean number of posts per student were significantly different each year except between 2019 and 2021 (at the 95% significance ($|t| > 2.0$)).

Table 7

Comparing the Mean Number of Posts with Social Presence Per Student Each Year

Year	Mean no. Posts per student	SD	t-test with 2018	t-test with 2019	t-test with 2020	t-test with 2021	t-test with 2022	t-test with 2023
2018	0.01	0.815		11.01	3.04	15.00	7.05	-3.57
2019	5.12	2.235	-11.01		-8.80	1.52	-6.21	-14.67
2020	1.57	1.235	-3.04	8.80		12.35	3.87	-7.72
2021	5.80	2.392	-15.00	-1.52	-12.35		-9.37	-21.00
2022	2.65	1.616	-7.05	6.21	-3.87	9.37		-13.81
2023	0	0	3.57	14.67	7.72	21.00	13.81	

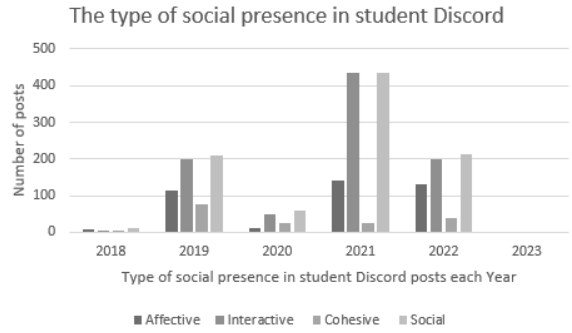
Most posts with social presence were seen in 2019 and 2021 which are not significantly different to one another. All other values are significantly different to 2023. There was a noticeable decrease in 2020 which could be related to the impact of the COVID-19 pandemic.

Categories of Social Presence

The occurrence of social presence was coded according to affective, interactive, or cohesive categories. There may have been more than one category relevant to the content of each post. In all but 2018, where 41.67% of the student posts were classified as interactive, the most prominent category was interactive which varied between 99.77% in 2021 and 82.76% in 2020. Prior to the pandemic the affective category was prominent (in 66.67% of posts in 2018 and 53.81% in 2019). The affective category was only evident in 18.97% of posts in 2020 and then increased to 32.42% of posts in 2021 and 61.03% of posts in 2022. Generally, the cohesive category was the least, varying between 5.52% of student posts in 2021 to 36.67% of student posts in 2019. During the pandemic (2020), the cohesive category was the highest in student posts with social presence at 43.1%. These are shown in Figure 4 and Table 8.

Figure 4a-b

The Numbers (A) and Percentages (B) of the Different Categories of Social Presence in Student Discord Posts for the Years 2018 To 2023.



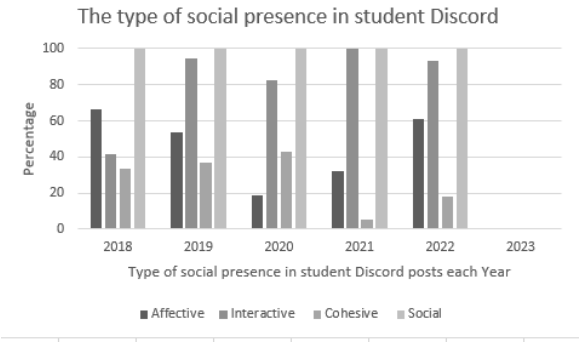


Table 8

The Different Categories of Social Presence in Student Discord Posts for the Years 2018 To 2023

Year	2018	2019	2020	2021	2022	2023
Affective	8 66.67%	113 53.81%	11 18.97%	141 32.41%	130 61.03%	0
Interactive	5 41.67%	199 94.76%	48 82.76%	434 99.77%	198 92.96%	0
Cohesive	4 33.33%	77 36.67%	25 43.10%	24 5.52%	39 18.31%	0
Social	12	210	58	435	213	0

Summary

Comparing the use of Discord as a discussion platform for a first-year game design university class with Canvas Discussions revealed that students posted more often in Discord and their posts were more likely to be coded as demonstrating social presence, particularly in the interactive category. The pandemic had a noticeable negative impact on the percentage of students who posted to Discord, suggesting that personal circumstances take precedence when students are in distress. This indicates that an online discussion tool alone is unlikely to resolve all engagement challenges

Discussion

There are benefits to being part of an online learning community, even for those students who do not participate. Students benefit not only from asking questions, but from observing the interactions of their peers, learning from the answers they receive, and feeling comforted by the realisation that others face similar challenges. Rinesko and Muslim (2020) found that lurkers (those students who follow discussions but do not post) can gain significant value by learning from their classmates. This suggests that regardless of the format, increased discussion within a course can benefit the entire cohort.

Variations in social presence between Discord and Canvas Discussions may be influenced by students' perceptions of these platforms. Research by Kahu et al. (2024) suggested that students felt more comfortable asking questions on Discord, viewing it as an informal space, whereas Canvas Discussions was perceived as a more formal, institutional platform. Discord was perceived to be a social media, rather than a formal communication channel (Heinrich et al., 2022). Students were relieved of the burden of formulating questions in a formal manner. A "key strength of Discord was that it sat outside the institutional space" (Kahu et al., 2024, p.309), creating an environment where students felt equal to staff. Our findings of greater social presence in Discord aligns with these observations, suggesting that the perceived informality of the platform helps to encourage student interaction.

A significant difference between the way that Canvas and Discord are perceived is the control of the discussion space and its functionalities. Canvas Discussions has the same features as many external tools: students can respond to questions, teachers are available to join discussions, and students can work together, but it allows less user control than Discord. Discord allows users to set up private spaces to use the service as a backchannel, a feature that students value (Kahu et al., 2024; Rinesko & Muslim, 2020). Canvas does not have this feature, nor does it allow students to include participants from outside their course, an option they have in their private Discord channels. However, the difference appears to be more about perception than functionality, raising the question of whether an institutional platform could ever provide the level of student autonomy that an external tool can. Kahu et al. (2024, p.310) noted that "student familiarity with a tool was also important" suggesting that student preferences may be related as much to their familiarity with the tool, as to its technical capabilities.

The specific tool may be less important than the students' prior experience and comfort in using it. In our study, most students were gamers and so were already familiar with Discord through gaming. Likewise, Rinesko and Muslim (2020) investigated the use of WhatsApp for course discussion and attributed its success to students' existing use of the app for personal communication. Kahu et al.'s comparison of Microsoft Teams and Discord found that Discord offered "wider disciplinary community" (2024, p.304), but Teams did not, which they attributed to a lack of student familiarity with the platform. This suggests that Kahu et al.'s (2024) proposed Learning Commons Communication Tool (LCCT) may struggle to reach the same levels of engagement as the technology that students already use in their everyday lives.

Discord's community building potential may extend beyond the immediate course cohort. Previous studies found that there was value in including class alumni in the discussion space (Vladoiu & Constantinescu, 2020) and incorporating students from other courses, as well as industry professionals (Kahu et al., 2024). Heinrich et al. (2022) pointed out that using Discord in conjunction with their LMS facilitated communication within the course itself, in student subgroups, and in the broader disciplinary cohort. Our implementation of Discord was more limited, restricting the server to current class members after an earlier incident, but the platform still facilitated stronger community interaction than did Canvas. Teachers can participate on either platform. Heinrich et al. (2022) observed that students valued the presence of their teachers, and Rinesko and Muslim (2020) noted that engagement from teaching staff increased engagement. However, it appears that the key factor is not the use of Canvas Discussions themselves, but the visibility of teachers engaging within student-oriented spaces rather than restricting their

presence to institutionally controlled platforms.

While Discord offered benefits for social presence, it also had its limitations. Students who were unfamiliar with the platform often struggled with navigation and locating stored material, which could present challenges in accessing course information and raise equity concerns. Our students were required to use their real names to participate in the Discord server, and Canvas is automatically tied to the students' university log in, so anonymity was not possible, a feature that Squires and Rigby (2024) found valuable for student engagement. Our institution discontinued use of Discord because of concerns about oversight. These concerns show the challenges of balancing informal, student-led spaces with institutional requirements for equity, accessibility, and control.

The researchers found the Community of Inquiry and within it the concept of social presence with its three categories: affective, interactive, and cohesive, to be a useful framework for exploring and explaining what the teaching staff using Discord and Canvas Discussions intuitively understood about the nature of student participation in these spaces. The template provided by Rourke et al. (1999) is still quite relevant to current studies in this area, however, minor modifications such as those outlined in Table 2 may need to be made to account for software affordances. Other scholars have also suggested variations to CoI. Aykol & Garrison (2019) replaced the *interactive* category with *open communication*. Whiteside's (2015) Social Presence Model emphasises emotional expression, interaction intensity, and instructor involvement. These dimensions were evident in our Discord data, particularly through humour, emojis, and informal peer support, yet were less visible in Canvas. This suggests that platforms like Discord surface affective and stylistic markers of engagement that exceed CoI's original categories. Garrison (2007) critiqued the original framework explaining that the nature of social presence should change over the duration of learning, as the cohort moves beyond socialisation and towards collaborating on common goals. Our data did not enable this degree of analysis, but these findings show that when Canvas was used as the conversation space, there was no social interaction at all. The distinction is between the absence or presence of social interactions, rather than between the quality of those interactions. However, we acknowledge that social interactions rely on factors beyond platform design, and are shaped by pedagogical choices, facilitator presence, and current contexts. Our analysis focused on empirical observations and cannot claim a direct causal link between the communication platform and learning outcomes.

Limitations

This study has several limitations. One contextual limitation is that the participant cohort consisted largely of game design students, many of whom were already familiar with Discord through personal use. This disciplinary context may have inclined students to adopt and engage with the platform more readily than students from other fields, limiting the generalisability of the findings. The study also spanned multiple years under differing conditions, which weakened the control of variables. From 2018 to 2021, the course included an embedded Alternate Reality Game (ARG), which may have inflated the number of posts and social presence indicators in those years; this activity was discontinued in 2022. The pandemic years (2020–2021) introduced further variation, as student behaviour and emotional states were likely shaped by lockdowns, stress, and digital fatigue.

Cohort sizes also varied considerably, from 17 to 75 students, and the number of tutors ranged from 1 to 3, creating differences in opportunities for participation and potential network effects. The changing context across the years of this study means that these conditions cannot be reproduced and the research, which was applied retrospectively to existing data, is not replicable.

There were also analytic limitations. Only two weeks of communication data (weeks 2 and 6) were analysed each year. While this approach aligns with the precedent set by Rourke et al. (1999) in using discrete weeks as representative samples, it may not capture the full variability of engagement across a semester. Finally, there were technical challenges in comparing Discord and Canvas due to differences in how interactions were recorded. For example, data exported from Discord did not include "likes," whereas Canvas posts did. However, in Canvas these likes were primarily used for voting or polling rather than as spontaneous expressions of engagement, making direct comparison between the two platforms problematic.

Conclusion

This study examined how the use of Discord, a popular server-based chat platform, impacted social presence across multiple iterations of a blended learning course. Between 2018 and 2022, when Discord was employed, student posts were consistently coded as demonstrating social presence, with particularly high levels in 2019, 2021, and 2022. Even in 2020, when engagement declined during the disruption of the COVID-19 pandemic, many posts still demonstrated social presence. Most posts fell into the interactive category, highlighting the capacity of informal, student-oriented communication platforms to facilitate peer exchange and sustain engagement over time.

In 2023, when the course transitioned to Canvas Discussions, no student posts were coded as demonstrating social presence. This contrast suggests that informal, student-oriented platforms provide stronger opportunities for interaction and community building, whereas institutionally controlled discussion boards appear less effective in supporting engagement. At the same time, the longitudinal data show that platform choice alone is not sufficient. Broader contextual factors, such as the pandemic, cohort size, and disciplinary culture, also shaped participation and levels of social presence. Taken together, these findings highlight both the potential and the limitations of Discord and underscore the importance of platform design and context when fostering social presence in blended learning environments.

When compared with Canvas Discussions, this research found that Discord increased both the total number of student posts and the number of posts coded as demonstrating indicators of social presence, consistent with the absence of such indicators noted above, which raises concerns about its effectiveness in fostering a sense of belonging between students. Discord posts coded as demonstrating social presence were most often classified in the "interactive" category, suggesting that the platform is particularly effective in promoting student-to-student exchange. At the same time, Discord is not a panacea for creating strong social bonds. In 2020, the year most affected by the COVID-19 pandemic, the mean number of student posts was lower than in the preceding and subsequent years, though still greater than the mean number of posts when Canvas Discussions was used. These findings highlight both the potential and the limitations of Discord and support further research into the platform's role in fostering social presence among university students.

Future Research

Future research could investigate whether similar outcomes could be achieved using institutional tools like Canvas Discussions when employed in the same informal way as platforms like Discord. This would help clarify whether the observed effects are a result of the platform itself or stem from students' familiarity with it. Additionally, it would be valuable to explore whether more experienced students, who are more accustomed to formal university communication platforms, are more likely to engage with these tools as they progress through their studies.

Beyond social presence, further work should also examine cognitive and teaching presence, exploring how these dimensions interact with one another across different platforms. Our observations suggest that teaching presence may be more visible in informal, student-oriented platforms because the higher volume of student contributions creates more opportunities for instructor responses. Similarly, the interactive exchanges facilitated by these platforms may offer greater scope for cognitive presence. However, these impressions were not formally analysed in this study and remain important avenues for future research.

While external communication platforms like Discord offer many benefits for building community and supporting peer interaction, they also pose risks related to bullying, harassment, and exclusion. Institutions must therefore consider how to manage these risks responsibly, including through clear behavioural guidelines, active moderation, and alignment with existing student conduct policies. Research into best practices for ensuring safety within informal online learning spaces would be valuable, particularly if universities increasingly adopt such platforms to enhance engagement.

Finally, because the students in this study were game design majors already familiar with Discord, it remains uncertain whether similar patterns of social presence would emerge in disciplines where students have less experience with such tools. Further research could investigate how varying levels of digital literacy, disciplinary culture, and prior exposure influence the effectiveness of informal communication platforms in fostering connection. These insights would support more inclusive and discipline-sensitive integration of platforms like Discord across higher education.

Declarations

Ethics Statement

This study was conducted in accordance with recognised ethical standards and approval was received from the University of the Sunshine Coast Human Research Ethics Committee (Approval number A231918). Informed consent was waived due to the retrospective nature of the research and the use of existing data. All data were generated and reported with respect for confidentiality and anonymity.

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interpretations are the authors' own. Data analysis, coding, and interpretation of results were conducted manually without the use of AI. All AI-assisted edits were reviewed and approved by the authors.

Conflict of Interest Statement

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

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Reducing Learner Disorientation in MOOC Learning Paths: Evidence from a Hybrid Recommender System

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Abstract
Nonlinear learning, which aligns with natural thinking and addresses individual needs, has great potential for e-learning. However, personalized learning paths in MOOCs through in-course recommenders remains limited, with only 18% adoption. Therefore, this research focuses on reducing learners' disorientation by creating personalized adaptive learning paths in MOOCs using a hybrid recommender system, combining ontology and PrefixSpan-based sequential pattern mining. A Moodle-based prototype was tested in a quasi-experimental design with three groups: (1) a comparison group using sequential learning without recommendations, (2) a nonlinear learning group using an ontology-based recommender system, and (3) a nonlinear learning group using a hybrid recommender system. Of 209 registrants, 102 actively participated and consented to data use. The results show that the hybrid recommender group had a higher average efficiency than the ontology recommender group, achieved the highest effectiveness in two of three sub-learning outcomes, and had higher mean scores on 22 of 30 e-learning satisfaction variables. Hypothesis testing with analysis of covariance (ANCOVA) showed no significant differences in efficiency, partial support for effectiveness (significant material access patterns but equivalent assessment scores), and partial support for satisfaction (significant differences in e-learning usability, Moodle preference, and learner behaviour). Visualization using weighted directed graphs of learning paths revealed similar forward-linear learning path patterns across all groups, except for variations in the first three modules of the comparison group. These findings underscore the potential of hybrid recommender systems to reduce learner disorientation, improve learner satisfaction and usability, and optimize learning paths in MOOCs. Future research should consider potential confounding variables such as course duration and sample size, as well as alternative configurations to maximize their benefits across various educational settings.

Keywords: Adaptive learning, hybrid recommender system, learning path, learner disorientation, MOOC, personalized learning

Rahayu, N. W., Kurniawan, I. N., Hidayah, I., Ferdiana, R., & Kusumawardani, S. S. (2026). Reducing learner disorientation in MOOC learning paths: Evidence from a hybrid recommender system. *Online Learning, 30*(3), 561-600. https://doi.org/10.24059/olj.v30i3.4956

Nonlinear learning refers to an approach in which learners themselves choose the learning materials, rather than following a sequence pre-defined by instructors (Blaschke & Hase, 2016; Peters, 2002). This approach offers flexibility, enabling learners to explore content aligned with their interests and needs. Although nonlinear learning paths can be beneficial and hold significant potential (Moore, 2020), they also risk causing learning disorientation—a sense of losing direction closely linked to learning outcomes and content structure (Correa, 2017). Therefore, some degree of structure remains necessary since the absence of structure can be equivalent to the absence of learning (Rootzén, 2015).

To minimize learning disorientation, learners (individually or in groups) may receive emotional support or technical competence reinforcement (Kaplan et al., 2021; Mamun et al., 2020; O'Brien & Reale, 2021). However, such support generally targets only a few individuals. This challenge is amplified in large-scale online learning contexts like Massive Open Online Courses (MOOCs). While MOOCs offer broad, inclusive access, their massive scale and diverse learner backgrounds make it harder to provide personalized learning experiences. Consequently, personalization technologies are crucial for improving learners' experiences in MOOCs.

Personalizing e-learning is more complex than in domains such as e-commerce, e-libraries, and e-government (George & Lal, 2019). Two major contributing factors are the dynamic nature of learners' profiles before, during, and after the learning process (Huang et al., 2019) and the limited availability of learner ratings for educational content (Lowenthal et al., 2015). In response, experts have developed various personalization technologies in e-learning—such as Intelligent Tutoring Systems, gamification, and recommender systems. Compared to other approaches, recommender systems can help learners save time by quickly identifying relevant materials from a large content pool (Tondello et al., 2017). Previous studies showed that hybrid recommender systems are becoming more common (George & Lal, 2019; Rahayu et al., 2023). However, studies specifically integrating ontology and sequential pattern mining to adapt to learners' evolving skills and preferences are still limited.

The remaining sections of this paper continue as follows: Section 2 provides a theoretical background and related works. Section 3 describes the research methods, including system architecture, experimentation, and analysis methods. Sections 4 and 5 detail the results that address the research questions and provide a discussion, respectively. Finally, Section 6 concludes the study.

Review of Related Literature

Nonlinear Learning Path

Learning path refers to the sequence of learning materials (Premlatha & Geetha, 2015; Rahayu et al., 2024). There are two types of learning path: linear, where topics are studied in a fixed order, and nonlinear, which allows learners to choose the sequence of topics for a more flexible approach (Robberecht, 2007).

Nonlinear learning utilizes hyperlinks (links) to enable nonsequential access to materials. In online learning environments, these links enhance cognitive processes by creating connections and context among materials, facilitating actions such as navigation, browsing, searching, connecting, collecting, annotating, and editing (Peters, 2002). Nonlinear students may find themselves disoriented by incoherent learning materials. Therefore, personalization is key to prevent such disorientation (Rahayu et al., 2024).

Learning Disorientation

Learning disorientation is the "tendency to lose direction in a nonlinear environment." This phenomenon can arise when learners encounter new uncertainties or perceive a lack of progress in their studies (Leroux et al., 2024). Previous research has identified two primary internal factors contributing to disorientation in nonlinear learning contexts. The first factor is a deficiency in visual-spatial abilities necessary for understanding the structure of information. The second factor involves a lack of metacognitive skills required to assess one's current learning position and determine the subsequent direction for learning (Correa, 2017).

Disorientation disrupts the learning process, causing learners to take longer to complete tasks (Correa, 2017). As a result, disorientation can negatively impact learning outcomes. Furthermore, disorientation is often unstable, irregular, and recurring, and it does not resolve spontaneously, thereby necessitating external support (Leroux et al., 2024).

Recommender Systems

Recommender systems are defined as tools and software techniques that provide suggestions to users based on their preferences and behaviors (Klašnja-Milićević et al., 2015). These systems operate by selecting the most relevant items through user- or item-based dependency principles (Aggarwal, 2016). In the e-learning domain, recommender systems serve as a means of personalization to enhance learner engagement (Huang et al., 2019), optimize academic performance (Harley et al., 2018), and support learners who are facing challenges (Huang et al., 2019).

Recommender systems can be broadly classified into two categories (Aggarwal, 2016): (1) basic recommender systems that utilize interaction data or attributes, and (2) domain-specific recommender systems that incorporate contextual factors. Basic recommender systems include content-based filtering (analyzing item attributes such as learning material topics or difficulty levels), collaborative filtering (using learner interaction patterns and ratings), knowledge-based systems (incorporating explicit learner preferences), and demographic-based approaches (considering learner characteristics). Domain-specific recommender systems extend these foundations by incorporating contextual information such as location, time sensitivity, spatial data, or social network structures.

The application of these recommendation techniques can be categorized into two approaches: standalone and hybrid. Standalone systems rely on a single technique from the basic classification, focusing on one type of data source or recommendation logic. Hybrid systems, in contrast, strategically combine multiple techniques to address two critical needs: (1) utilizing all available knowledge from diverse data sources (such as learner profiles, interaction histories, and contextual information), and (2) compensating for the limitations of individual techniques by leveraging their complementary strengths (Aggarwal, 2016). These hybrid systems can be designed through three structured approaches: ensemble (combining outputs from multiple techniques), monolithic (integrating techniques within a unified algorithm), or mixed designs. Research shows a growing preference for hybrid recommenders, particularly in learning path recommendations (George & Lal, 2019; Rahayu et al., 2023), as they can better address the complexity of personalized learning needs.

Developing effective e-learning recommender systems, however, remains challenging due to the scarcity of learner-provided ratings for educational materials (Salehi et al., 2013). This lack of data complicates material ranking (Aggarwal, 2016) and necessitates advanced methods to address the gap. Knowledge-based artificial intelligence, such as ontology, has

proven valuable for overcoming these limitations and supporting personalized recommendations (George & Lal, 2019; Tarus et al., 2018). In the context of learning path recommenders, ontology has been used both as the foundation for standalone systems (Hnida et al., 2014; Romero et al., 2019) and as a key component of hybrid systems (Colace et al., 2020; Vesin et al., 2013).

The performance of recommender systems, evaluated in controlled environments and online experiments, is typically measured across three categories (Erdt et al., 2015): system performance, which includes the accuracy and coverage of the recommendations provided; effects on learning, covering aspects such as efficiency, effectiveness, and learner motivation; and user-centric effects, encompassing learner satisfaction and the perceived usefulness of the recommendations.

Related Work

Based on our systematic literature review of 35 articles retrieved from Google Scholar (search conducted July 19, 2024, using keywords: "recommender" in MOOC), we identified 28 research papers and 7 review papers. Analysis of the research papers revealed that the majority (23 out of 28, or 82%) of recommender systems on MOOC platforms focus on course recommendations, while the remaining systems (5 out of 28, or 18%) target in-course learning components (see Table 1; complete dataset in Appendix A).

Table 1

In-Course Recommender Systems on MOOC Platforms

Recommended Items	Recommender Techniques
Concepts, Meta-concepts	Knowledge graph (Wu et al., 2024), a combination of ontology and deep learning models (Bidirectional Encoder Representations from Transformers or BERT) (Tazi et al., 2023), and a combination of knowledge graphs and deep learning models (Sentence-BERT) (Alatrash et al., 2024)
Learning activities	Markov Decision Process (Amin et al., 2023)
Discussion forums	Knowledge graphs with LightGBM (He et al., 2023)

Several studies, including those related to learning-path recommendations, have noted the increasing use of hybrid recommender systems (George & Lal, 2019; Rahayu et al., 2023; Tarus et al., 2018). Even so, developing recommender systems in the e-learning domain faces an additional challenge, namely that learners seldom provide explicit ratings for learning materials (Salehi et al., 2013). This limited number of ratings complicates ranking-based recommendations (Aggarwal, 2016), suggesting the need for knowledge-based techniques such as ontology (George & Lal, 2019; Tarus et al., 2018). Referring to the proposed recommender-system classification (Aggarwal, 2016), ontology collaborators in hybrid recommender systems can be grouped into model-based collaborative filtering (Colace et al., 2020; Colace & De Santo, 2010; El-Bouhdidi et al., 2013; Vesin et al., 2013), neighborhood-based collaborative filtering (Vesin et al., 2013), content-based recommender (Capuano & Toti, 2019), and others.

Although collaborative filtering has been widely implemented, this study adopts a different perspective by considering findings that learners' abilities and preferences may change over time (Huang et al., 2019). Accordingly, this hybrid recommender model

combines ontology as a knowledge base with sequential pattern mining to incorporate time-based contexts. This combination is expected to produce more adaptive recommendations than a single-technique recommender system.

This study aims to reduce learning disorientation by implementing a hybrid recommender system that integrates ontology (knowledge-based recommender technique) with sequential pattern mining (time-sensitive recommender technique). By combining these approaches, we expect to generate more adaptive recommendations than a single-method recommender system could provide. To evaluate this, we conducted an experiment with three groups: (1) a comparison group following a sequential learning path without a recommender system, (2) a nonlinear learning path group with an ontology-based recommender, and (3) a nonlinear learning path group using a hybrid recommender.

Given that learning disorientation often correlates with low learning outcomes (Shih et al., 2012), we assessed the hybrid system's effects on learning—specifically efficiency and effectiveness—as well as user-centric effects such as satisfaction. In addition, we explored how learners navigated through the materials, particularly whether they tended toward linear or nonlinear paths. Based on these objectives, we address four research questions (RQs):

- **RQ1**: Do learners using the hybrid recommender system achieve higher learning efficiency compared to those using the ontology-based system or no recommender system?
- **RQ2**: Do learners using the hybrid recommender system achieve higher learning effectiveness than those using an ontology-based system or no recommender system?
- **RQ3**: Do learners using the hybrid recommender system report higher satisfaction levels than those using an ontology-based system or no recommender system?
- **RQ4**: How do learners navigate the learning paths when accessing materials and completing assessments?

Methods

System Architecture

This study develops and evaluates an e-learning recommender system that supports nonlinear learning paths, essential for adapting to learners' evolving abilities and preferences over time (Huang et al., 2019). These dynamics are reflected in time-based learning behavior patterns, revealing implicit preferences for specific materials. The system employs ontology to manage the coherence of learning materials (Rahayu et al., 2022) and integrates PrefixSpan, a sequential pattern mining algorithm, to capture and predict individual learning sequences based on temporal behavior (Aggarwal, 2016).

Recommender systems must be customized to the specific platform they are deployed on (Aggarwal, 2016; Oliveira, 2016). In this study, we implement our system within the Moodle LMS environment, chosen for its widespread use in many countries (Fernando, 2020). Moodle's extensive user base also allows our recommender model to be potentially replicated in various learning contexts.

Case Study: Database Course

In this research, the recommender system was adapted and tested to recommend learning paths for Database courses. We selected the Database domain because it is a core subject in various computer science–related programs (Ishaq et al., 2023),and to date, it has not been explored in studies focused on learning paths (Rahayu et al., 2023). Nonetheless, choosing the Database domain does not limit the recommender system's application, as the system can be implemented in a wide range of learning environments that support nonlinear or nonsequential learning (Hase, 2016).

The Database materials used in this case study refer to the international curriculum document created by ACM/IEEE, namely, the Computing Curricula 2020. The analysis results indicate that the most frequently studied topics among six disciplines are data models, database systems, SQL queries, and SQL data definitions. These four topics form the basis of the course learning outcomes.

In our implementation, we consolidated these four topics into three sub-learning outcomes (Sub-LO) to create a more coherent pedagogical structure, as illustrated in Figure 1. The mapping is as follows:

1. Sub-LO-1: This learning outcome combines the topics of data models and database systems, focusing on students' ability to design relational database models at conceptual, logical, and physical levels. These two topics are integrated because students need to understand database system fundamentals before they can effectively design data models.

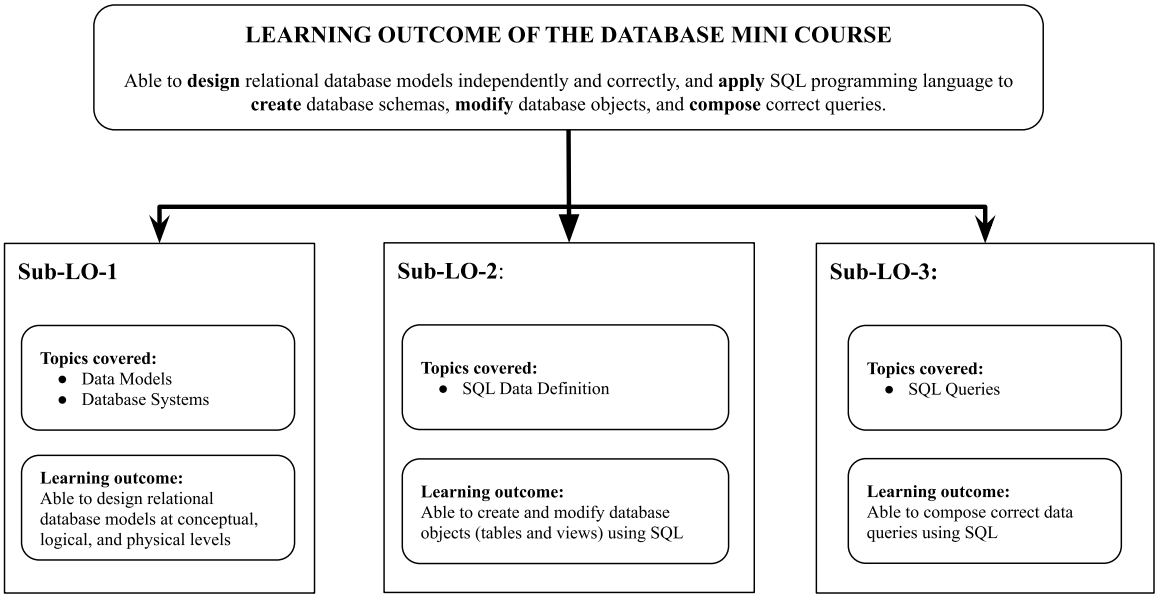
2. Sub-LO-2: This learning outcome addresses the SQL data definition topic, enabling students to create and modify database objects (tables and views) using SQL.

3. Sub-LO-3: This learning outcome covers the SQL queries topic, focusing on students' ability to compose correct data queries using SQL.

These three sub-learning outcomes comprise 11 modules, which include 11 assessments and 97 pages of material.

Figure 1

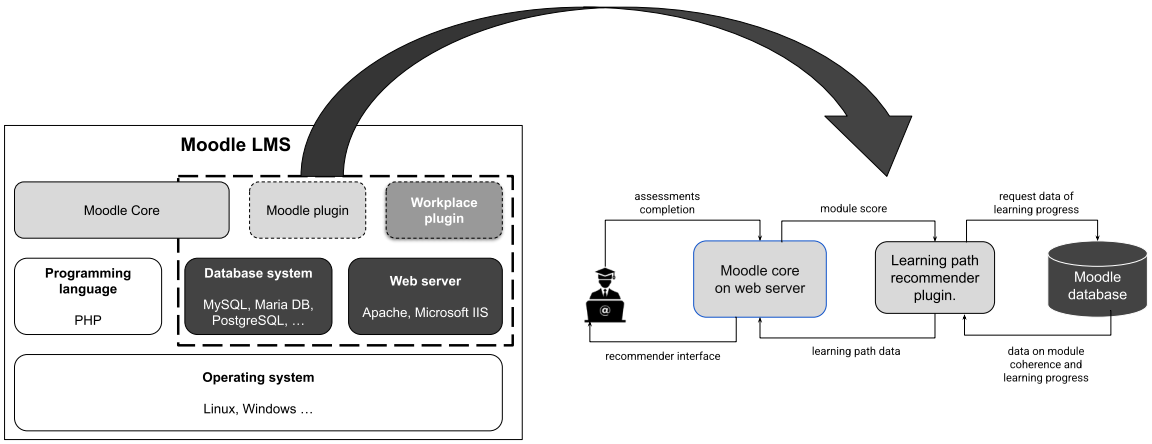
Learning Outcome Structure for Database Mini Course



The recommender system was developed as a Moodle plugin to allow direct integration without modifying Moodle's core, thus making updates easier and new features more flexible to add (Moodle, 2024). Technically, this recommender plugin runs on the web server; its programming code is stored in the *dirroot* directory, and the plugin-related data is maintained in a database (Buchner, 2022) (see Figure 2).

Figure 2

Interaction Between Recommender System and Moodle Components (adapted from Buchner, 2022)

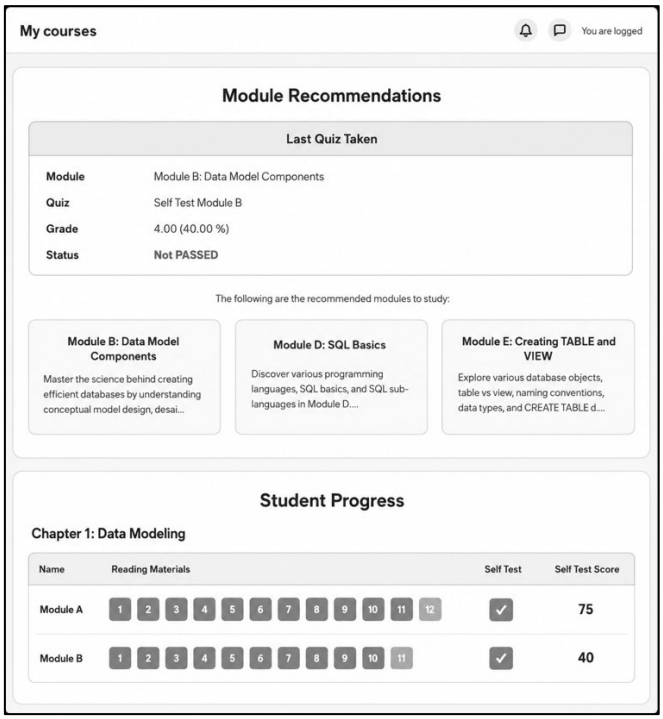


The interfaces of both standalone ontology-based and hybrid recommender systems are similarly designed. Figure 3 shows an example where a learner who has not yet passed Module B receives recommendations to continue their studies by retaking Module B and

studying Modules D and E. These recommendations appear as blue-colored text with hyperlinks.

Figure 3

Interface of Recommender Plugin



Participants

A total of 209 learners enrolled and were assigned to three groups: comparison group AC (n = 149), ontology-based recommender group B (n = 28), and hybrid recommender group D (n = 32). Due to the voluntary nature of the MOOC, participation decreased across stages, with 136 learners logging in and 121 providing informed consent for data use. Given learner autonomy in selecting materials and assessments, final sample sizes varied by measurement as shown in Table 2. This variation reflects authentic MOOC engagement patterns where learners independently choose which activities and assessments to complete.

Table 2

Participant Flow and Sample Sizes by Measurement

Stage/Measurement	Group AC	Group B	Group D	Total
Enrolment & Consent				
Enrolled	149	28	32	209
Logged in	97	17	22	136
Consented to data use	87	16	18	121
Efficiency Measures				
accessDuration	74	15	13	102
assessmentDuration	73	14	12	99

Effectiveness Measures				
materialPercentage	74	15	13	102
subLO1Score	75	14	13	102
subLO2Score	54	12	7	73
subLO3Score	51	11	6	68
finalScore	73	14	12	99
Satisfaction				
Survey respondents	35	10	8	53

Note: Sample sizes vary across measurements due to learners' autonomy in completing optional course materials and assessments.

Experimental Design

The prototype of the nonlinear learning path recommender system was evaluated through an online experiment to assess user responses and system effectiveness (Tedre & Moisseinen, 2014). This experiment was important due to the limited availability of relevant e-learning datasets (Tarus et al., 2017).

The experiment involved real learners in a database MOOC. A total of 230 learners across Indonesia registered voluntarily through an online form. The study included participants who were at least 18 years old. The age requirement ensured that learners had developed the self-regulation skills necessary for nonlinear learning (Lowe et al., 2013). After removing duplicates and invalid entries, 209 registrants were accepted. Despite extending the registration period, only 60 learners engaged in nonlinear learning (28 in Period I and 32 in Period II).

Dividing these learners into four groups across the two periods—control and experimental groups for each period—resulted in groups that were too small (Vesin et al., 2013). Therefore, the study utilized one comparison group (Isnawan, 2020) and two nonlinear groups without random assignment, classifying it as a quasi-experiment (Field & Hole, 2002). We implemented a posttest-only nonequivalent group design with covariates (Reichardt, 2019; Rogers & Révész, 2019), where the pretest captured stable traits such as demographics, and the post-test consisted of module assessments.

Demographic and participant characteristic variables were collected to serve as covariates for statistical control (see Section 3.6 for specific variables used in each analysis). Additionally, experimental group participants completed an initial profiling that captured their self-perceived competence and content preferences; this profiling informed the recommender system's personalized module sequencing but did not serve as a baseline outcome measure. The comparison group followed a linear learning path without profiling or system recommendations. Module assessments served as the posttest outcome measure for both groups.

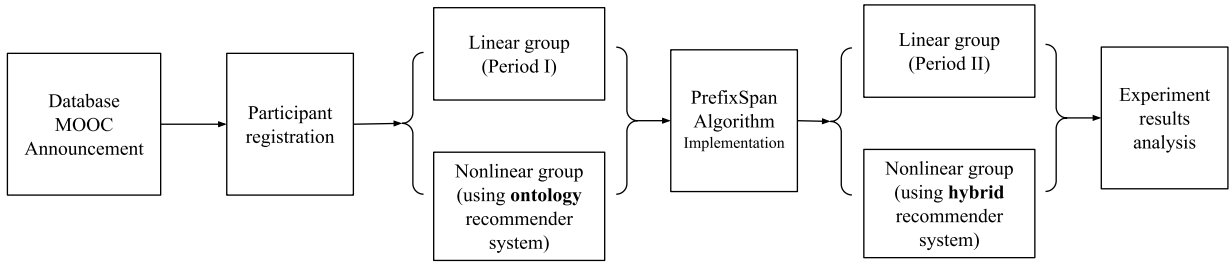
Consent for data use was obtained from all learners, who were informed that their data would be anonymized for scientific evaluation and publication. Those who did not consent were excluded to prevent selection bias.

Experimental Procedure

The experiment was conducted in phases and learners were divided into two periods with different schedules, learning methods, and recommender systems. However, three aspects remained consistent to ensure controlled results: course content, assessments, and instructor interactions. The experiment phases (Jing et al., 2022) are shown in Figure 4.

Figure 4

Summary of Experimental Procedure



Specifically, the experiment aimed to evaluate the impact of the recommender system by comparing three groups:

1. Comparison group: Learners following a linear (sequential) learning path without a recommender system (Period I and II).

2. Ontology-based recommender group: Learners using an ontology-based recommender system (Period I).

3. Hybrid recommender group: Learners using a hybrid recommender system (Period II).

Recommendations in the hybrid system were generated using learners' assessment results and the successful learning paths of their peers during the first period. To enhance learner success, mitigation strategies were implemented that not only adhered to e-learning design recommendations (Cagiltay et al., 2020) but also provided additional incentives upon successful completion, including e-money balances and certificates (Gong et al., 2021). The e-money balance was awarded through a lottery to learners who passed the course, while certificates were provided in two categories:

- Participation certificate (Hasso Plattner Institute, 2023): Given to learners who completed at least 60% of the material and 35% assessments.

- Award certificate (Coursera, 2021): Awarded to learners who completed at least 60% of the material and all assessments with a minimum score of 70 points.

Research variables used in the experiment include independent variables (types of learning path recommender systems) and dependent variables of effects on learning and user-centric effects (Erdt et al., 2015). Effects on learning are evaluated based on learning efficiency and effectiveness, while user-centric effects are assessed through the level of learner satisfaction. The dependent variables for each dimension are detailed as follows:

1. Learning efficiency refers to the time required for students to achieve the course learning outcomes. It was measured by the access time of the first and last materials (accessDuration) (Jerz, 2018) and the duration to complete assessments (assessmentDuration).

2. Learning effectiveness in achieving the learning objectives is measured by the number of materials visited and the assessment scores obtained (Rahayu et al., 2023; Vesin et al., 2013). The assessment scores used include formative scores for each sub-learning outcome as well as the final score (Erdt et al., 2015; Sudijono, 2015). Therefore, effectiveness is measured using five variables: percentage of material accessed, scores of sub-learning outcomes, and final score.

3. Perceived satisfaction: All learners were surveyed on their perceptions of general e-learning, while those in both recommender groups also answered additional questions about the recommender feature. Therefore, measurement is conducted using two types of instruments:

    a. General e-learning satisfaction: Measured using 30 statements in the Evaluating E-learning System Success (EESS) model, which includes six constructs: Technical System Quality (TSQ), Information Quality (INQ), Service Quality (SRQ), Support System Quality (SUP), Learner Quality (LER), and Instructor Quality (INS) (Al-Fraihat et al., 2020).

    b. Satisfaction with the recommender systems: Assessed through Recommender System (REC) construct which includes one essay question on whether the learning experience met learners' expectations (REC2) and three additional questions addressing the frequency of use (REC3), perceived benefits (REC4), and overall satisfaction (REC5).

Analysis Method

The first three research questions were examined through hypothesis testing using inferential statistical methods, while RQ4 was addressed by visualizing the learning paths for each group. The three specific hypotheses are outlined below:

- H1: Learners using the hybrid recommender system achieve better learning efficiency than those using an ontology-based system or no recommender system.

- H2: Learners using the hybrid recommender system achieve better learning effectiveness than those using an ontology-based system or no recommender system.

- H3: Learners using the hybrid recommender system achieve better satisfaction levels than those using an ontology-based system or no recommender system.

For RQ1, RQ2, and RQ3, we conducted Analysis of Covariance (ANCOVA) to assess the differences in learning efficiency, learning effectiveness, and satisfaction levels, respectively, among the three groups. ANCOVA was chosen because it controls for covariate variables that might influence the results, providing a more accurate estimate of the treatment effect. Following ANCOVA, post hoc tests were performed to identify specific group differences where significant effects were detected.

The quasi-experimental approach used in this study has limitations regarding internal validity, although it maintains strong external validity (Reichardt, 2019). One challenge to internal validity is the potential bias arising from natural differences among learners before the treatment (i.e., the use of the recommender system). To address this, we identified factors that might influence the results (referred to as covariates) to minimize potential selection bias.

The covariates for the efficiency and effectiveness dimensions differ from those for the satisfaction dimension to accommodate the distinct constructs being measured and to address variations in data completeness. For efficiency and effectiveness, we used four covariate variables collected during registration: age range, field of study, participation period, and province. In contrast, the satisfaction dimension included six covariates collected through the survey: age range, field of study, participation period, gender, activity or job, and experience using the Moodle platform.

As a supplementary analysis, we examined prior knowledge as an additional covariate for RQ1-RQ2. Prior knowledge was measured through a self-assessment of competency across three course topics (data modeling, data definition language, and SQL queries) using a three-level scale (Beginner = 1, Intermediate = 2, Advanced = 3). A composite prior knowledge score (range 1-3) was calculated as the mean across topics. This analysis was limited to the two recommender groups (n = 24) who completed the optional assessment, as the comparison group did not. This supplementary analysis could not be conducted for RQ3 due to anonymous survey administration.

Our analysis began by testing the assumption of data homogeneity. When this assumption was met, we used Analysis of Covariance (ANCOVA). If the homogeneity assumption was not satisfied, we employed the Kruskal-Wallis test to handle data that do not meet parametric assumptions. We also used a significance level (p value) of 0.05 for our statistical analysis. This means that results with a p value less than 0.05 are considered statistically significant, indicating a meaningful difference or relationship unlikely to have occurred by chance. In addition to the p value, we reported effect sizes to show whether the differences were not only significant but also substantial in magnitude.

We addressed RQ4 by applying visualization techniques that employ weighted directed graphs to uncover patterns in learners' behaviors. The learning path graphs were created using navigation log data, which included records of accessed materials and completed assessments. This data was subsequently organized into inter-module matrices. To enhance clarity, matrices were based on the number of modules (11 × 11) rather than the number of material pages (97 × 97). Internal module transitions were normalized by dividing the total accesses by the number of materials within the module.

The size of the nodes and the thickness of the edges in the graphs correspond to the matrix values, reflecting the number of accesses to each material or assessment. Additionally, the directionality in the graphs helps reveal whether learners followed linear or nonlinear paths in their learning.

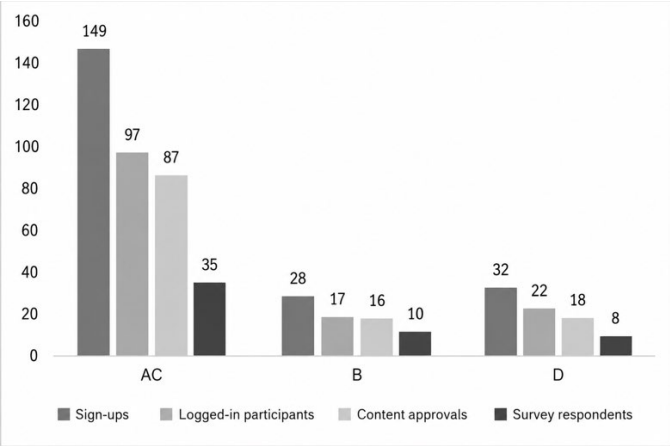
Results

Demography

Figure 5 illustrates the trend of decreasing learner numbers in each group: comparison (Class A Period I, Class C Period II), nonlinear learning path with ontology-based recommender (Class B), and nonlinear learning path with hybrid-based recommender (Class D). Class AC experienced a reduction in login learners by up to 34.9%, with 10 learners withholding data consent. Class B recorded only a 60.7% login rate, while Class D achieved 68.7%. By the end of the experiment, 136 learners had logged in at least once, and 121 of them consented to data.

Figure 5

Participant Flow Showing Declining Enrollment Across Stages for Comparison (AC), Ontology-based (B), and Hybrid (D) groups.

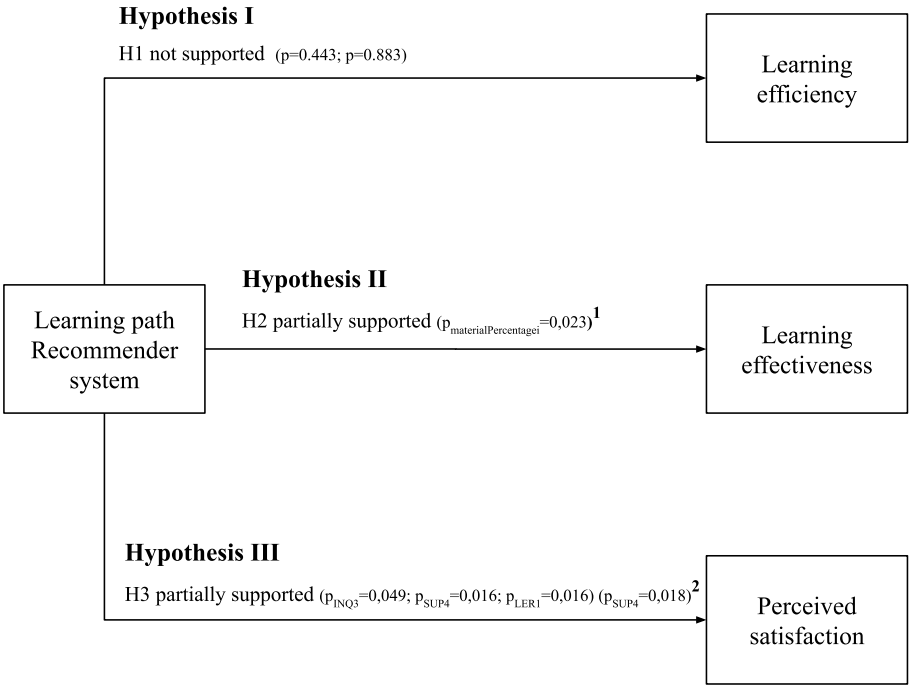


Note: Sample sizes for efficiency and effectiveness measurements are detailed in Table 2.

Of the 121 learners, the majority (77%) were aged 18–24 years, followed by those over 40 years old (11%), then 25–30 years (6%), and 31–40 years (6%). Additionally, 85.1% of learners were from the Design and Engineering disciplines. In the nonlinear groups (Class B and D), 74.3% of learners reported being beginners in Database learning. A total of 102 out of 121 learners were recorded as actively engaging in learning activities. Recapitulation of Moodle log data reveals varied participation, from accessing materials to completing assessments. Of all learners, 53 completed the satisfaction survey, with most being undergraduate students (n = 33).

Figure 6

Research Model with Hypothesis Testing Results



1. Hypothesis 2 was measured by five variables. Results show for `materialPercentage` (p = 0.023); the other four variables are not significant.
2. Hypothesis 3: The hybrid recommender group showed significantly higher satisfaction than the ontology-based group in INQ3, SUP4, and LER1 ($p < 0.05$), but not in other satisfaction variables. The ontology-based group showed significantly higher satisfaction than the comparison group only in SUP4 (p = 0.018).

Figure 6 presents the overall hypothesis testing results across the three dimensions. H1 (efficiency) was not supported, while H2 (effectiveness) and H3 (satisfaction) received partial support. Detailed analyses for each research question are presented in the following subsections.

> **RQ1:** Do learners using the hybrid recommender system achieve higher learning efficiency compared to those using the ontology-based system or no recommender system?

This study measures efficiency based on study time usage, specifically using the variables accessDuration (n = 102) and assessmentDuration (n = 99), as detailed in Table 2. Class B (*M* = 9953.5; *SE* = 1117.7) accessed materials for the longest duration, whereas Class AC (*M* = 7574.9; *SE* = 459.5) and Class D (*M* = 7591.5; *SE* = 851.7) had nearly identical access durations. Additionally, Class B (*M* = 52.9; *SE* = 9.5) completed assessments in the longest time compared to Class D (*M* = 44.3; *SE* = 10.7) and Class AC (*M* = 42.7; *SE* = 6.5). Since efficiency is inversely related to access duration or assessment duration, the ontology-based recommender group exhibited lower learning efficiency compared to the other two groups.

Table 3

ANCOVA Results for Group Differences in AccessDuration and AssessmentDuration

Dependent variable	F	df	p	ηp²	Significant covariates
accessDuration	0.822	2, 95	.443	.017	Period (p = .038)
assessmentDuration	0.124	2, 92	.883	.003	none

Note. All group effects tested with df = (2, residual df). Covariates controlled: Age, Field of Study, Period, and Province. Only significant covariates are reported in the table.

Statistical significance tests on learning efficiency using ANCOVA (Table 3) revealed that:

1. The comparison group, ontology-based recommender group, and hybrid-based recommender group did not show significant differences in material reading access duration (p = .443; ηp² = .017).

2. The comparison group, ontology-based recommender group, and hybrid-based recommender group also did not exhibit significant differences in assessment completion duration (p = .883; ηp² = .003).

3. The participation period in the experiment had a significant effect (p = .038; ηp² = .045) on material access duration.

These results indicate that there are no significant differences in material access duration and assessment completion duration among three groups. Therefore, the hypothesis addressing RQ1 (“Do learners using the hybrid recommender system achieve higher learning efficiency compared to those using the ontology-based system or no recommender system?”) is not supported.

> **RQ2:** Do learners using the hybrid recommender system achieve higher learning effectiveness than those using an ontology-based system or no recommender system?

Learning effectiveness was measured using five variables: materialPercentage (n = 102), subLO1Score (n = 102), subLO2Score (n = 73), subLO3Score (n = 68), and finalScore (n = 99), as detailed in Table 2. The effectiveness levels across the three groups varied. First, the hybrid recommender group achieved the highest average scores in sub-learning outcomes of subLO2Score (M = 7.786; SE = 0.535) and subLO3Score (M = 7.758; SE = 0.601). Second, the ontology-based recommender group obtained the highest material access percentage (M = 0.786; SE = 0.094), subLO1Score (M = 7.371; SE = 0.552), and finalScore (M = 6.588; SE = 0.734).

To address potential confounding effects of prior knowledge, we conducted supplementary analyses for RQ1 and RQ2 using only the two recommender groups with prior knowledge data (n = 24). Prior knowledge was measured as a composite score (range 1-3) based on self-assessed competency across three course topics. Results showed that prior knowledge was not a significant covariate for any efficiency or effectiveness outcomes (all p > .05). Specifically, for efficiency: accessDuration (p = .648, ηp² = .010) and assessmentDuration (p = .873, ηp² = .001). For effectiveness: materialPercentage (p = .424, ηp² = .031) and other measures similarly showed no significant effect. Group differences between the two recommender systems remained non-significant, consistent with the main

three-group analysis. These findings suggest that prior knowledge did not substantially influence the observed treatment effects (see Appendix B).

Table 4

ANCOVA Results for Group Differences in Learning Effectiveness

Dependent variable	F	df	p	ηp²	Significant covariates
materialPercentage	3.872	2, 95	.024*	.075	Period (p = .009)
subLO1Score	1.836	2, 95	.165	.037	none
subLO2Score	0.170	2, 66	.844	.005	Age (p = *.030)*
subLO3Score	2.061	2, 61	.136	.063	none
finalScore	2.440	2, 95	.093	.049	none

Note. All group effects tested with df = (2, residual df). Covariates controlled: Age, Field of Study, Period, and Province. Only significant covariates are reported in the table.

Table 5

Post Hoc Comparisons - Group

		Mean Difference	SE	t	p_{tukey}
AC	B	-0.151	0.112	-1.350	0.371
	D	0.286	0.117	2.444	0.043*
B	D	0.438	0.163	2.689	0.023*

Analysis of learning effectiveness through statistical significance testing (Table 4 and Table 5) showed that:

1. ANCOVA results revealed a significant group difference in material access percentage (p = .024; ηp² = .075), with Period as a significant covariate (p = .009). Post-hoc Tukey tests indicated that the hybrid recommender group (Group D) accessed significantly less learning material compared to both the comparison group (Group AC, p = .043) and the ontology-based recommender group (Group B, p = .023). No significant difference was found between the comparison and ontology-based groups (p = .371).

2. The comparison group, ontology-based recommender group, and hybrid recommender group did not show significant differences in sub-learning objective 1 scores (p = .165; ηp² = .037).

3. The three groups also did not exhibit significant differences in sub-learning objective 2 scores (p = .844; ηp² = .005), although Age was a significant covariate (p = .030).

4. Similarly, no significant group differences were found for sub-learning objective 3 scores (p = .136; ηp² = .063).

5. The comparison group, ontology-based recommender group, and hybrid recommender group did not demonstrate significant differences in final course scores (p = .093; ηp² = .049), though the result approached significance.

Based on the above data, the hypothesis addressing RQ2 ("Do learners using the hybrid recommender system achieve higher learning effectiveness compared to those using the ontology-based system or no recommender system?") is partially supported. While the hybrid recommender system significantly influenced material access patterns (1 of 5 effectiveness measures), it did not result in superior learning outcomes as measured by assessment scores. The recommender system appeared to facilitate more efficient material selection without demonstrably improving learning effectiveness.

> **RQ3:** Do learners using the hybrid recommender system report higher satisfaction levels than those using an ontology-based system or no recommender system?

RQ3 examined learner satisfaction through two complementary analyses (see Table 2 for sample sizes). First, general e-learning satisfaction was assessed across all three groups using the EESS model (six constructs: TSQ, INQ, SRQ, SUP, LER, INS) with reliability analysis, radar charts, and ANCOVA (n = 53). Second, recommender-specific satisfaction was evaluated using the REC construct (n = 18), comparing only the hybrid and ontology-based groups through radar charts and qualitative feedback.

Reliability analysis using Cronbach's alpha (N= 53) indicated high internal consistency for four constructs: INQ (Information Quality, α = .857), TSQ (Technical System Quality, α = .846), SRQ (Service Quality, α = .845), and INS (Instructor Quality, α = .837). The LER (Learner Quality) construct demonstrated acceptable reliability (α = .741), while SUP (Support System Quality) showed questionable reliability (α = .659). All constructs except SUP met the acceptable reliability threshold of $\alpha \geq .70$. Detailed item-level statistics are presented in Table 6.

Table 6

Satisfaction Items: Reliability, Descriptive Statistics, and ANCOVA Results Across Three Groups

Construct	Item	Group AC	Group B	Group D	Cronbach alpha	F	*p*	ηp²	Sig. Covariates
TSQ	TSQ1	4.54(0.61)	4.3(0.68)	4.25(0.71)	0.846	.684	.510	.030	Gender (p = .038)
	TSQ2	4.29(0.67)	3.9(0.74)	4.25(0.46)		.426	.656	.019	
	TSQ3	4.26(0.74)	4.1(0.88)	4.63(0.52)		.647	.528	.029	
	TSQ4	4.2(0.72)	3.9(0.74)	4.13(0.64)		.657	.523	.029	
	TSQ5	4.17(0.82)	3.8(0.92)	4.38(0.52)		.254	.777	.011	
INQ	INQ1	4.29(0.57)	4.1(0.74)	4.13(0.64)	0.857	.668	.518	.029	
	INQ2	4.14(0.65)	3.6(0.7)	4.13(0.64)		.804	.454	.035	Gender (p = .023)
	INQ3	4.23(0.73)	4(0.67)	4.5(0.54)		3.003	.060	.120	Period (p = .033)
	INQ4	4.23(0.69)	3.8(0.63)	4.5(0.54)		2.266	.116	.093	
	INQ5	4.23(0.84)	3.9(0.88)	4.13(0.64)		.290	.749	.013	
	INQ6	4.37(0.6)	3.9(0.88)	4.5(0.54)		2.244	.118	.093	
	INQ7	4.03(0.82)	3.8(1.03)	4.38(0.52)		1.168	.320	.050	Field of study (p = .035)
SRQ	SRQ1	4.09(0.82)	3.9(0.74)	4.13(0.84)	0.845	.083	.921	.004	

	SRQ2	4.14(0.69)	4.1(0.74)	4.38(0.52)		1.727	.019	.073	
	SRQ3	4.43(0.56)	4.2(0.63)	4.25(0.46)		.670	.517	.030	Employment status ($p < .001$)
	SRQ4	4.31(0.63)	4.1(0.74)	4.25(0.46)		1.102	.341	.048	
	SRQ5	4.23(0.65)	3.9(0.74)	4.25(0.46)		1.155	.325	.050	
SUP	SUP2	4.17(0.71)	3.8(0.63)	4.38(0.52)	0.659	2.218	.121	.092	
	SUP3	4.38(0.7)	4.1(0.57)	4.38(0.52)		1.270	.291	.056	
	SUP4	4.2(0.68)	3.6(0.7)	4.38(0.52)		4.799	.013	.179	
LER	LER1	4.29(0.67)	3.8(0.63)	4.63(0.52)	0.741	4.292	.020	.016	
	LER2	4.34(0.73)	4.1(0.32)	4.5(0.54)		.175	.840	.008	
	LER3	4.43(0.66)	4.1(0.57)	4.63(0.52)		1.072	.351	.046	
	LER4	4.29(0.8)	4.4(0.52)	4.25(0.71)		.137	.873	.006	
	LER5	4.29(0.52)	4.1(0.99)	4.5(0.54)		1.134	.331	.049	
INS	INS1	4.49(0.56)	4.4(0.52)	4.75(0.46)	0.837	.974	.386	.042	
	INS2	4.43(0.61)	4.4(0.52)	4.75(0.46)		.860	.430	.038	
	INS3	4.46(0.66)	4.1(0.74)	4.5(0.76)		.596	.555	.026	
	INS4	4.31(0.72)	4.2(0.63)	4.63(0.52)		1.038	.363	.045	
	INS5	4.46(0.66)	4.5(0.53)	4.75(0.46)		.707	.499	.031	

Average construct scores were plotted in radar charts using Microsoft Excel 16.82, with the following explanations:

1. The hybrid recommender group provided the highest satisfaction perception for TSQ (Figure 7a) in the variables of "Meeting learner needs" ($M = 4.63$) and "System component integration" ($M = 4.38$). The comparison group gave the highest satisfaction score for "Ease of learning" ($M = 4.25$).

2. The hybrid recommender group dominated INQ (Figure 7b) in the variables of usability (M = 4.50), content clarity (M = 4.50), up-to-date content (M = 4.50), and content design quality (M = 4.38).

3. Similar findings were obtained for SRQ (Figure 7c), especially in the variable of online support availability ($M = 4.38$).

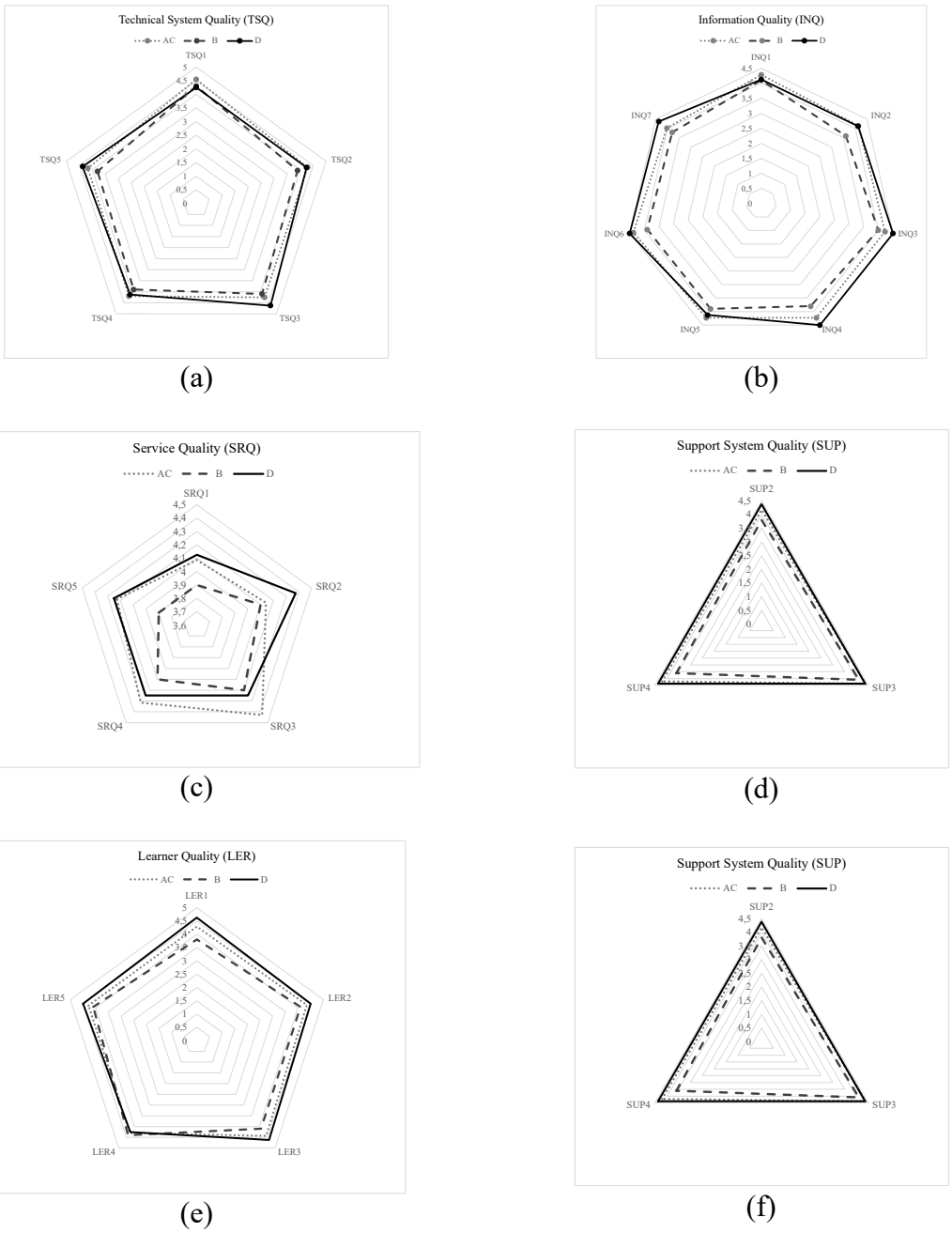
4. Satisfaction perceptions of the hybrid recommender group and the comparison group regarding SUP were relatively similar (Figure 7d).

5. The hybrid recommender group provided the highest satisfaction perception for four out of five variables in the LER construct (Figure 7e), namely, learner behavior (M = 4.63), learner attitude (M = 4.50), learner anxiety (M =4.63), and self-efficacy (M =4.50).

6. The hybrid recommender group (Figure 7f) excelled in the INS construct.

Figure 7

Radar Charts of General E-Learning Satisfaction Constructs: (a) TSQ, (b) INQ, (c) SRQ, (d) SUP, (e) LER, (f) INS



The results in Table 6 and the radar chart in Figure 7 indicate that the hybrid recommender group achieved higher average satisfaction compared to the ontology-based recommender group. However, most of the satisfaction comparisons between three groups did not show significant differences, except for:

1. A significant difference was found between Class D (hybrid recommender group) and Class B (ontology-based recommender group) in the following variables:

INQ3 (usability of e-learning; t = 2.431, p = .049), SUP4 (preference for Moodle; t = 2.885, p =.016), and LER1 (learner behavior; t = 2.902, p = .016).

2. Class B (ontology-based recommender group) significantly differed from Class AC (comparison group) in the SUP4 variable (preference for Moodle; t = -2.857; p =.018).

Several variables also influenced learners' satisfaction with the recommender system:

- Gender had a significant effect on TSQ1 (ease of use; p = .038; ηp^2 = .094) and INQ2 (accessibility of e-learning; p = .023; ηp^2 =.112).
- The participation period had a significant effect (p = .033; ηp^2 = .099) on the usability of e-learning (INQ3).
- Field of study had a significant effect (p = .035; ηp^2 = .097) on content design quality (INQ7).
- Learners' activity or employment status had a significant effect (p< .001; ηp^2 = 0.222) on IT team readiness (SRQ3).

Figure 8 shows a radar chart comparing the hybrid and ontology-based groups across the REC construct. Satisfaction specific to the recommender-assisted groups was measured using the Recommender System (REC) construct, with 80% of learners in Class B and 100% in Class D willing to respond. All learners also provided positive feedback to the essay question "Does non-sequential learning align with your expectations?" although the wording of the responses varied (Table 7).

Figure 8

Radar Chart of Perceived Satisfaction Across REC Constructs

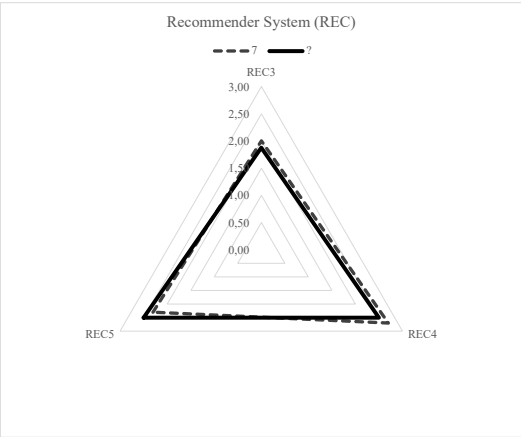


Table 7

Alignment with Learners' Learning Expectations (REC2)

No	Category	Number of learners	Responses
1.	Agree	14	• Satisfactory

2.	Strongly agree	2	• Effective enough as I don't really like learning in a sequential manner. • In general, satisfactory. • Overall, it matches my expectation. • Yes, I can start with the easiest tasks first, and it's more enjoyable. • Perfectly meets my expectations because I can access it anytime and anywhere. • Perfectly matches my expectations as the recommendations are helpful.

Based on the above data, the hypothesis addressing RQ3 ("Do learners using the hybrid recommender system report higher satisfaction levels compared to those using the ontology-based system or no recommender system?") is supported by the INQ3, SUP4, and LER1 variables in comparisons between the recommender groups, but not by other variables. Additionally, in comparisons between the ontology-based recommender group and the comparison group, the hypothesis is only supported by the SUP4 variable but not by others.

RQ4: How do learners navigate the learning paths when accessing materials and completing assessments?

Graph-based analysis was conducted to identify patterns in learners' paths. These learning path graphs were generated from navigation log data for materials and assessments. While material navigation logs were readily available in Moodle, assessment logs required a custom plugin specifically developed for this experiment.

A complete set of normalized frequency matrices for all classes is shown in Figure 9. Class A and Class C served as comparison groups for Periods I and II, respectively, while Class B and Class D represented the ontology-based and hybrid recommender groups. Navigation graphs for materials in each class are shown in Figure 10.

Figure 9

Navigation Data: (a) Class A and (b) Class C (comparison groups); (c) Class B and (d) Class D (recommender groups).

Modul	A	B	C	D	E	F	G	H	I	J	K
A	**85**	**62**	6	7	0	2	1	0	0	0	1
B	**27**	**53**	**36**	4	2	0	1	2	0	1	0
C	7	7	**40**	**29**	1	2	1	1	0	0	1
D	3	4	7	**38**	**25**	1	1	0	0	0	1
E	1	2	1	1	**28**	**26**	2	0	0	0	0
F	2	2	1	1	4	**24**	**25**	0	0	1	0
G	1	1	0	1	0	3	**27**	**22**	2	2	2
H	0	1	1	0	1	0	1	**24**	**23**	0	0
I	1	0	0	0	0	1	1	1	**24**	**20**	3
J	1	0	0	1	0	1	1	1	1	**27**	**20**
K	2	1	3	1	1	0	0	3	2	5	**21**

(a)

Modul	A	B	C	D	E	F	G	H	I	J	K
A	**64**	**60**	5	3	1	0	2	1	0	3	0
B	**19**	**56**	**43**	5	3	2	2	1	6	1	1
C	6	**11**	**37**	**33**	0	0	0	1	0	1	1
D	1	2	3	**45**	**34**	3	1	1	0	0	0
E	1	3	0	2	**36**	**32**	1	2	0	1	1
F	2	3	1	1	3	**31**	**28**	0	0	0	2
G	2	1	0	1	0	2	**35**	**35**	0	0	0
H	1	1	0	0	1	1	6	**35**	**30**	0	2
I	1	6	0	1	0	0	0	1	**33**	**32**	0
J	0	1	0	0	0	0	0	0	2	**37**	**36**
K	2	3	1	0	1	0	2	0	6	4	**34**

(b)

Modul	A	B	C	D	E	F	G	H	I	J	K
A	**32**	**18**	3	0	0	0	0	0	2	0	1
B	4	**19**	**13**	5	2	0	1	0	0	1	1
C	2	4	**15**	**10**	3	0	0	0	0	0	1
D	1	3	0	**20**	**11**	1	0	0	0	0	1
E	0	3	1	1	**18**	**10**	0	1	0	1	1
F	0	0	0	0	0	**16**	**10**	1	4	1	2
G	0	0	0	0	0	1	**15**	**11**	2	0	1
H	0	0	0	1	0	2	2	**12**	8	1	0
I	1	0	0	0	0	2	1	0	**13**	**12**	3
J	0	1	0	0	1	0	0	1	0	**16**	**11**
K	2	3	3	0	2	3	1	0	3	1	**10**

(c)

Modul	A	B	C	D	E	F	G	H	I	J	K
A	**28**	**22**	2	3	0	0	0	0	1	0	0
B	4	**22**	**18**	3	0	0	0	0	0	0	0
C	2	4	**14**	**11**	2	0	0	0	0	2	1
D	2	1	1	**17**	9	0	4	0	1	0	0
E	1	0	1	0	**13**	8	2	0	0	0	0
F	0	1	0	0	1	**16**	8	0	0	0	2
G	1	1	0	1	1	1	**16**	**11**	3	1	0
H	0	0	0	0	0	1	1	**15**	**10**	0	0
I	2	0	0	1	0	1	2	1	**12**	**10**	2
J	2	0	0	0	0	1	0	0	1	**13**	**10**
K	2	1	1	0	0	0	1	0	4	1	**11**

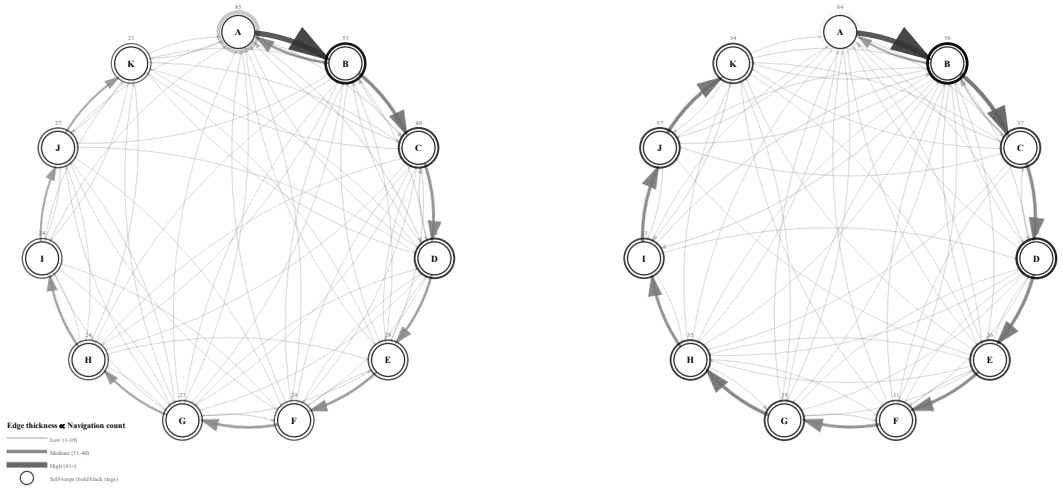
(d)

Learning path patterns in the recommender groups slightly differed from those in the comparison group. This indicates that, besides frequently accessing materials within the same module, learners in the comparison group navigated both forward (e.g., from Module A to Module B) and backward (e.g., from Module B to Module A) between modules. Some learners even alternated directions; for example, after reading Module B, many moved forward to Module C, while others returned to Module A.

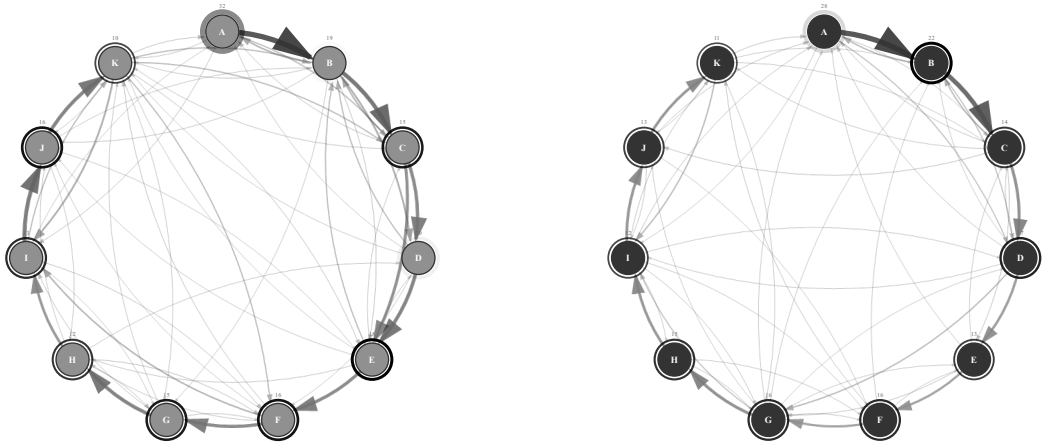
Learning path graphs for the recommender groups show that, in general, learners moved forward to other modules in alphabetical order (referred to as linear forward). For example, learners in the ontology-based recommender group typically progressed from Module A to Module B and read Module J after Module I. Similarly, learners in the hybrid recommender group exhibited a similar pattern. This visualization (Figure 10) also shows that the graph of the ontology-based recommender group appears slightly more complex. However, both recommender groups followed the same linear progression: Module A to Module B to Module C, and so on. Overall, navigation data and graphs show similar linear forward learning paths across all four classes, except for the first three modules in the comparison group.

Figure 10

Learning Path of Accessed Materials: (a) Class A and (b) Class C (comparison groups); (c) Class B and (d) Class D (recommender groups).



(a) (b)



(c) (d)

Note: Edge thickness represents navigation frequency between modules, with arrows indicating direction. Bold black rings indicate within-module navigation (self-loops). Legend shown in (a) applies to all subplots.

This study presents matrices for the two experimental classes, with learning paths recorded using the recommender system plugin. Navigation matrix data (Figure 11a and 11b) highlight frequencies in specific table cells, where cells with more than five assessment attempts are marked in orange. These orange cells indicate repeated attempts on the same assessment. For instance, cell [B, B] in Class B has a value of 6, showing that six learners repeatedly attempted Module B's assessment. Overall, Class B and Class D differ in repetition patterns: assessments for Modules B, C, and K are frequently repeated in Class B, while Modules B, C, F, H, I, J, and K are popular for repetitions in Class D.

Figure 11

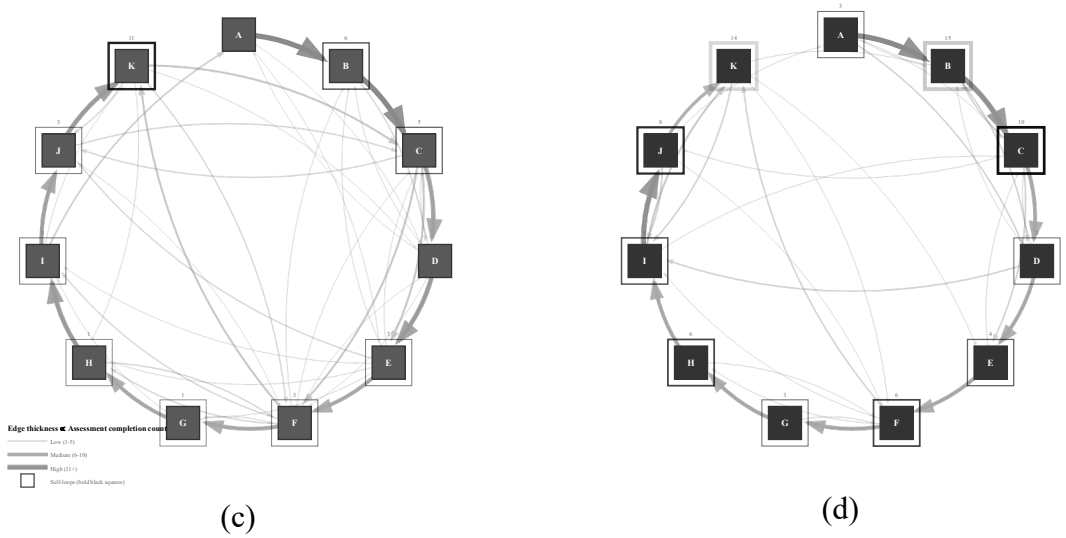
Assessment Completion and Learning Patterns for Classes B and D (recommender groups).

Modul	A	B	C	D	E	F	G	H	I	J	K
A	0	14	0	1	1	0	0	0	0	0	0
B	0	6	14	2	0	0	0	0	0	0	0
C	0	0	5	10	4	4	0	0	0	2	0
D	1	1	1	0	11	1	0	0	0	0	0
E	0	1	1	0	3	9	1	1	1	2	0
F	0	1	1	1	0	3	9	2	2	0	4
G	0	0	0	0	0	1	1	9	1	0	0
H	0	0	0	0	0	2	0	1	11	0	0
I	3	0	0	0	0	0	0	0	3	10	1
J	0	0	2	0	0	1	0	0	0	3	11
K	0	0	4	1	0	2	0	1	0	2	11

(a)

Modul	A	B	C	D	E	F	G	H	I	J	K
A	3	11	1	2	0	0	0	0	0	0	0
B	1	15	10	2	0	0	0	0	0	0	0
C	0	2	10	7	2	0	0	0	0	1	0
D	0	1	1	3	7	0	0	0	2	0	0
E	0	0	1	0	4	7	0	0	0	0	0
F	0	0	0	0	0	6	7	1	1	0	2
G	0	0	0	0	0	1	3	7	0	0	0
H	0	0	0	0	0	1	0	6	7	0	0
I	0	0	1	0	0	0	0	0	5	10	3
J	1	0	0	0	0	1	0	0	2	8	6
K	0	1	0	0	1	1	0	0	2	0	14

(b)



(c) (d)

Note: (a,c) Class B; (b,d) Class D. (a,b) Assessment completion matrices; (c,d) assessment navigation graphs. Edge thickness indicates completion frequency; arrows indicate direction; bold black squares = self-loops. Legend shown in (c) applies to all subplots.

Visualization of assessment learning paths (Figure 11c and 11d) shows that assessment completion patterns in Classes B and D resemble material access navigation, following a linear forward order. The result shows that learners in the recommender groups generally completed assessments for Module A, then proceeded sequentially to Module B, C, and so on, until reaching Module K. However, matrix data indicate that learners in the ontology recommender group completed assessments 5% more frequently by using 15.2% more varied paths. Thus, the conclusions are:

1. Most learners in the recommender groups accessed materials and completed assessments in a linear forward path.

2. The ontology-based recommender group completed assessments with more varied nonlinear paths.

3. The hybrid recommender group more frequently repeated assessments for the same module, resulting in a 21% shorter average assessment completion duration.

Discussion

Evaluating recommender systems is a complex domain (Erdt et al., 2015), and the performance of different recommender systems in e-learning is difficult to compare (da Silva et al., 2023; George & Lal, 2019). Therefore, this study has aimed to employ more detailed evaluation metrics than previous studies by specifying measurement constructs, utilizing learner performance data recorded in the system, and adopting a more comprehensive e-learning evaluation framework (Al-Fraihat et al., 2020).

Recommender systems can be evaluated through offline experiments with datasets, user studies in controlled settings, or online experiments (real-life testing) involving real learners. Previous studies indicate that most recommender systems are assessed using offline methods and user studies (da Silva et al., 2023; Erdt et al., 2015; Rahayu et al., 2023). This

study, evaluated through online experiments and employing a quasi-experimental design, contributes to understanding system performance in real-life conditions.

The experiments measured the recommender system's performance in terms of efficiency, effectiveness, and satisfaction. These metrics were analyzed using descriptive statistics and hypothesis tests (ANCOVA or Kruskal-Wallis), depending on data distribution. The diverse evaluation approaches, variable dimensions (Erdt et al., 2015), and different statistical techniques compared to previous studies (e.g., *t* tests (Jevremovic et al., 2017), ANOVA (Jeng & Huang, 2019)) provide a comprehensive perspective on recommender system performance.

Descriptive statistics revealed that the hybrid recommender group had the second-highest efficiency after the comparison group. However, hypothesis testing after controlling for covariates showed no significant differences among the three groups. In the assessmentDuration variable, the hybrid group completed assessments 21% faster than the ontology recommender group, likely due to improved assessment layouts based on feedback from Period I. Clearer assessment questions facilitated easier retakes for the hybrid group, aligning with findings that unclear instructions hinder online learners (Kelly et al., 2024; Roy et al., 2020).

The results show no support for H1 (efficiency) and partial support for H2 (effectiveness). The hybrid group accessed significantly fewer materials ($p = .023$) but achieved equivalent assessment scores, indicating the system influenced learning behavior without improving outcomes. These findings partially contradict research showing hybrid recommender systems enhance learning effectiveness outcomes (Colace & De Santo, 2010; Deschênes, 2020; Jevremovic et al., 2017; Vesin et al., 2013), while aligning with studies showing varied outcomes (Murad et al., 2020). Factors such as short course duration and small sample size may have influenced results. The findings suggest that advantages of the hybrid approach are contextual and depend on measured variables; thus, the hybrid approach is not universally superior to single-method approaches (ontology-based).

The satisfaction evaluation showed the hybrid recommender group scored highest in 22 out of 30 e-learning satisfaction variables. This may be attributed to learning path suggestions and progress tracking features, which reduce extraneous cognitive load by simplifying module selection (Premlatha & Geetha, 2015; Sweller et al., 2011) and visually clarifying learning progress. These features likely made learners feel their progress was important and navigable, leading to higher satisfaction (Sartor et al., 2020; Smith, 2018). Specifically, the hybrid group scored an average of 2.5 out of 3 on benefits (REC4) and overall satisfaction (REC5) in the recommender system variables (REC2 - REC5).

Additionally, 89% of learners in both recommender groups reported that the system met or exceeded their expectations, surpassing 65–65.6% satisfaction rates in other studies (Colace et al., 2020; Vesin et al., 2013). The hybrid recommender group also achieved higher overall satisfaction scores (REC5), though perceptions of frequency and benefits were lower than the ontology-based recommender group. This suggests that satisfaction may be influenced by other factors, such as cognitive styles (Betoret, 2007) or learner needs (Al-Azawei et al., 2016).

The analysis of the learning path graph for course materials reveals that the patterns across the three groups are similar, exhibiting a forward linear path, except for the first three modules in the comparison group. Consequently, although the system provides the option to

select materials nonlinearly, learners in the experimental groups accessed the materials in an order comparable to that of the comparison group. One possible explanation for this phenomenon is B.F. Skinner's theory of operant conditioning (Huang et al., 2019). This theory suggests that learners, all over 18 years old, have previously experienced sequential learning processes during their primary and secondary education years (Rohman & Muhtamiroh, 2022). This established condition makes it difficult to alter such habitual behaviors.

Another significant finding is the presence of several confounding variables that influenced the measurement results:

1. Period of Participation: significantly affects access duration (efficiency dimension), the percentage of materials accessed (effectiveness dimension), and e-learning usability (satisfaction dimension).
2. Participant Age: significantly influences the score of sub-learning outcome II (effectiveness dimension).
3. Gender: impacts the ease of use and accessibility of e-learning (satisfaction dimension).
4. Field of Study: affects the quality of content design (satisfaction dimension).
5. Participant Activity or Occupation: influences the IT team's readiness (satisfaction dimension).

These findings align with previous research on the effects of participation period (Sibanda & Donnelly, 2014), age (Kintu et al., 2017), gender (Aliyu et al., 2019), field of study (Li et al., 2018), and learner activity (Alnaji & Karsu, 2016) on learning outcomes. However, it is noteworthy that these five confounding variables only influenced 1–3 out of the 40 dependent variables measured in this study. As a result, the overall impact of these confounding factors on the research outcomes remains inconclusive.

Implications

This study highlights important insights into designing and applying hybrid recommender systems in e-learning environments. While the collaboration between ontology and sequential pattern mining did not deliver the expected performance gains, the findings reveal practical considerations for educators and system designers. Specifically, aligning recommender systems with specific learning approaches, selecting appropriate artificial intelligence techniques, and ensuring robust experimental setups are critical for improving system efficacy. These results offer actionable guidance for personalizing learning paths.

The observed similarity in learning path patterns despite the availability of nonlinear material selection options suggests that habitual learning behaviors, as explained by operant conditioning, may persist even in more flexible learning environments. This has important implications for the design of e-learning recommender systems, indicating that merely providing nonlinear options may not be sufficient to change established learning behaviors. Future systems should consider incorporating strategies that actively encourage exploration and deviation from linear paths to fully utilize the potential of nonlinear learning environments.

The identification of confounding variables highlights the complexity of evaluating e-learning recommender systems. The significant impact of participation period, age, gender, field of study, and learner activity or occupation suggests that these factors should be carefully controlled or accounted for in future studies to isolate the effects of the recommender systems themselves. Additionally, understanding how these variables interact with system performance can inform more personalized and adaptive recommender strategies that cater to diverse learner profiles.

Limitations and Future Directions

This study was limited by several factors, including a small sample size, the presence of confounding variables, and a constrained experimental duration. These limitations affected the hybrid system's performance and the generalizability of the findings. To address these challenges, future research should investigate larger learner cohorts, test diverse combinations of recommender techniques, and extend the duration of experiments. Reducing confounding variables and improving the experimental setup will also enhance the reliability of results and provide deeper insights into hybrid recommender systems' effectiveness in real-world e-learning contexts.

Prior knowledge data were not systematically collected across all experimental groups, limiting our ability to control for this factor in the main three-group comparisons. Supplementary analyses with the two recommender groups (n = 24) showed no significant effect of prior knowledge, though the reduced sample size limits generalizability. Additionally, satisfaction surveys were administered anonymously to protect privacy, preventing linkage with prior knowledge or demographic data and limiting examination of individual-level factors. Future studies should implement systematic prior knowledge collection across all conditions while maintaining privacy protections through alternative means such as secure linking codes.

This study involved learners aged over 18 years, based on the assumption that individuals at this age generally possess self-regulated learning skills (Lowe et al., 2013). However, not all learners in this experiment exhibited strong self-regulation levels, which may have affected the performance of the recommender system. Initial screening could be conducted to ensure learners have sufficient self-regulation abilities. This step is expected to enhance the relevance and accuracy of experimental results regarding nonlinear learning path recommender systems.

The hybrid recommender systems combine learning path suggestion and progress tracking features. To increase learner engagement and completion rates, progress tracking features can be developed into gamification elements in e-learning (Meşe & Sevilen, 2021; Strmečki et al., 2015), as gamification has been shown to enhance motivation and sustained participation. Additionally, these features can be expanded into knowledge tracing to measure learners' knowledge status as it evolves over time (Huang et al., 2019; Shen et al., 2022).

Conclusion

This study assessed the effectiveness of e-learning recommender systems within a Database MOOC, comparing a comparison group, a single-method ontology-based recommender group, and a hybrid recommender group combining ontology and sequential pattern mining. The experimental results demonstrate that the hybrid recommender system surpassed the ontology-based system in efficiency, achieved the highest effectiveness in several sub-learning outcomes, and obtained the best scores in 22 out of 30 general e-learning

satisfaction variables. Furthermore, ANCOVA revealed significant differences in user satisfaction across three variables: e-learning usability (INQ3), Moodle preference (SUP4), and learner behavior (LER1), providing partial support for the satisfaction hypothesis. The effectiveness hypothesis was also partially supported, with the hybrid group accessing significantly fewer materials (p =.023), though this behavioral difference did not translate into superior assessment scores. No significant differences were observed in efficiency. These findings suggest that while hybrid recommender systems can influence learning behaviors and enhance specific aspects of user satisfaction, their impact on learning outcomes may be limited or contextual. The results emphasize the importance of tailoring recommender systems to specific learning environments and learner profiles, and distinguishing between process-level improvements and outcome-level effectiveness in evaluating recommender system performance. Future research should consider the identified confounding variables and explore alternative configurations for hybrid recommender systems to maximize their benefits across various educational settings.

Furthermore, the study identified five confounding variables (period of participation, age, gender, field of study,and learner activity or occupation) that affected a subset of the dependent variables. This highlights the complexity of evaluating e-learning systems and the need to account for diverse learners' characteristics in future research.

List of Abbreviations

ACM	Association for Computing Machinery
ANCOVA	Analysis of Covariance
ANOVA	Analysis of Variance
EESS	Evaluating E-learning System Success
IEEE	Institute of Electrical and Electronics Engineers
INS	Instructor Quality
INQ	Information Quality
LER	Learner Quality
LMS	Learning Management System
MOOC	Massive Open Online Course
SQL	Structured Query Language
SRQ	Service Quality
SUP	Support System Quality
TSQ	Technical System Quality

Declarations

Ethics Statement

Formal ethics board approval was not obtained prior to data collection. All participants provided informed consent to participate and for their anonymized data to be used for research purposes. All data were anonymized and handled to protect participant privacy.

Availability of Data and Materials

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Conflict of Interests

The authors declare that they have no competing interests.

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Authors' Contributions
NW: Methodology, formal analysis, investigation, writing - original draft, writing - review & editing. IN: Resources. IH: Validation. RF: Funding acquisition. SS: Conceptualization, Methodology, Supervision.

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Appendix A

Complete List of Analyzed Articles from Systematic Literature Review on MOOC Recommender Systems

No	Year	Authors	Title	Type	In-course recommender	DOI/URL
Part A: Research papers - In-course recommender systems (n=5; 18%)						
1	2023	Alatrash, R., Chatti, M. A., Ain, Q. U., Fang, Y., Joarder, S., & Siepmann, C.	ConceptGCN: Knowledge concept recommendation in MOOCs based on knowledge graph convolutional networks and SBERT	Research	Yes	Link
2	2023	Amin, S., Uddin, M. I., Alarood, A. A., Mashwani, W. K., Alzahrani, A., & Alzahrani, A. O.	Smart E-learning Framework for Personalized Adaptive Learning and Sequential Path Recommendations Using Reinforcement Learning	Research	Yes	Link
3	2023	He, J., Liu, Z., Chen, X., Wang, Y., & Zhang, M.	A novel link prediction approach for MOOC forum thread recommendation using personalized pagerank and machine learning	Research	Yes	Link
4	2023	Tazi, K., Azzouzi, S., & Charaf, M. E. H.	An Ontology-based Recommender System for Identifying Learners' Confusion in MOOCs	Research	Yes	Link
5	2024	Wu, X., Jiang, H., Zhang, R., Wang, Y., & Chen, L.	KAMC: Knowledge-Aware Meta-Concept Recommendation	Research	Yes	Link
Part B: Research papers - Course recommender systems (n=23; 82%)						
6	2023	Amin, S., Uddin, M. I., Mashwani, W. K., Alarood, A. A., Alzahrani, A., & Alzahrani, A. O.	Developing a personalized E-learning and MOOC recommender system in IoT-enabled smart education	Research	No	Link
7	2023	Garcia Cuco, A.	Recommender system for online courses	Research	No	Link
8	2023	Li, Y., Xiong, H., & Zhang, Y.	MHRR: MOOCs Recommender Service With Meta Hierarchical Reinforced Ranking	Research	No	Link
9	2023	Madhavi, A., Nagesh, A., & Kumar, P.	Efficient Course Recommendation using Deep Transformer based Ensembled Attention Model	Research	No	Link
10	2023	Mansouri, N., Soui, M., & Abed, M.	SFS feature selection with decision tree classifier for massive open online courses (MOOCs) recommendation	Research	No	Link
11	2023	Midhun Chakkaravarthy, D. G.	A Quality of Experience-based Recommender System for E-learning Resources	Research	No	Link
12	2023	Mohammad, U., Hamdan, Y., & Al-Masri, A.	A Novel Algorithm for Professor Recommendation in Higher Education	Research	No	Link
13	2023	Murad, D. F., Toha, M., & Rahman, A.	The Impact of Recommendation System Provided Based on Online Learning Readiness in the MOOC Environment	Research	No	Link
14	2023	Ul Haque, M. M., & Kotaiah, B.	A Cluster Based Recommendation System for MOOCs	Research	No	Link
15	2023	Wang, Q., Xiong, A., & Chen, L.	Design and Application of Online Courses under the Threshold of Smart Innovation Education	Research	No	Link

16	2023	Yang, B., & Qi, C.	A Personalized Course Recommendation System has been Developed Using xDeepFM and RoBERTa Models	Research	No	Link
17	2024	Alatrash, R., Chatti, M. A., Ain, Q. U., & Joarder, S.	Transparent Learner Knowledge State Modeling using Personal Knowledge Graphs and Graph Neural Networks	Research	No	Link
18	2024	Gupta, C., Khalaf, O. I., & Kumar, S.	MOOCRec_Sys: An Empirical E-learning Paradigm on Online Open Course using Sentiment Analysis and OWA operator	Research	No	Link
19	2024	Hao, L., Abdipoor, S., & Rahman, M.	Hybrid Graph Neural Networks with LSTM Attention Mechanism for Recommendation Systems in MOOCs	Research	No	Link
20	2024	Khalid, A.	Scalable and Practical Recommender System in Massive Open Online Courses (MOOCs)	Research	No	Link
21	2024	Lowe, D., Galhotra, B., & Smith, A.	Leveraging Recommender Systems to Tailor Moocs for Student Needs: A Data-Driven Approach	Research	No	Link
22	2024	Ma, W., Zhao, Y., & Chen, X.	Cascaded Knowledge-Level Fusion Network for Online Course Recommendation System	Research	No	Link
23	2024	Nurakhmadyavi, S. M. K. H.	Course Recommendation on Online Learning Platforms using Collaborative Filtering and Content-based Filtering with Implicit Feedback	Research	No	Link
24	2024	Rao, J., & Borchers, C.	Coursera-REC: Explainable MOOCs Course Recommendation using RAG-facilitated LLMs	Research	No	Link
25	2024	Rao, J., & Lin, J.	RAMO: Retrieval-Augmented Generation for Enhancing MOOCs Recommendations	Research	No	Link
26	2024	Sun, J., Mei, S., & Liu, H.	Prerequisite-enhanced category-aware graph neural networks for course recommendation	Research	No	Link
27	2024	Zhou, W., Zhou, X., Li, Y., & Wang, H.	Online Course Recommendation by Exploring User Interaction and Course Description	Research	No	Link
28	2024	Ain, Q. U., Chatti, M. A., Meteng Kamdem, P. A., Alatrash, R., Joarder, S., & Siepmann, C.	Learner Modeling and Recommendation of Learning Resources using Personal Knowledge Graphs	Research	Full text N/A	Link
Part C: Review papers (n=7, excluded from percentage analysis)						
29	2023	Asfaw, Z., Alemneh, D. G., & Tefera, B.	Data-Driven Decision-Making and Its Impacts on Education Quality in Developing Countries: A Systematic Review	Review	-	Link
30	2023	Cisel, M. T.	On the Ethical Issues Posed by the Exploitation of Users' Data in MOOC Platforms: Capturing Learners' Perspectives	Review	-	Link
31	2023	El Aouifi, H., El Hajji, M., & Es-Saady, Y.	Video-Based Learning Recommender Systems: A Systematic Literature Review	Review	-	Link
32	2023	Kumar, H., & Kumar, S.	Persistent Technologies Like Modified E-learning and MOOC Recommender System in IoT-Enabled Smart Education	Review	-	Link
33	2023	Maryam, O., Ashraf, H., & Khan, A.	Improved E-learning Based Recommender Systems: A Survey	Review	-	Link

34	2024	Bin, Q., Zuhairi, M. F., & Ahmad, N.	A Comprehensive Study On Personalized Learning Recommendation In e-learning System	Review	-	Link
35	2024	Boufaida, S. O., Benmachiche, A., & Kazar, O.	An Extensive Examination of Varied Approaches in E-learning and MOOC Research: A Thorough Overview	Review	-	Link

Appendix B

Supplementary ANCOVA Results with Prior Knowledge

Variable	N	Group effect			Prior knowledge effect		
		F	p	ηp²	F	p	ηp²
Efficiency							
accessDuration	24	1.453	.242	.010	.214	.648	.010
assessmentDuration	24	.063	.804	.003	.026	.873	.001
Effectiveness							
materialPercentage	24	.960	.338	.044	.666	.424	.031
subLO1Score	24	.254	.619	.012	.954	.340	.043
subLO2Score	18	.836	.375	.053	.016	.901	.001
subLO3Score	17	.003	.954	2.439×10^{-4}	1.457	.247	.094
finalScore	24	.681	.418	.031	.315	.581	.015

Empowering Educators: A Pilot Study on AI Literacy in K–12 Professional Development

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Abstract
As artificial intelligence (AI) continues to reshape modern society, there is an urgent need to equip K–12 educators with the skills and confidence to integrate AI tools into their instructional practice. This pilot study examined the preliminary effectiveness of an asynchronous professional development course designed to increase educators' comfort with AI, shift their perceptions, and expand access to instructional resources. A mixed-methods approach was used to analyze data from 30 participants, including K–12 teachers, preservice educators, and others in educational roles in K–12 schools, who completed pre- and post-course surveys. Quantitative results revealed statistically significant increases in comfort with AI, perceptions of AI, access to resources, and familiarity with AI tools. Correlational analyses found strong positive relationships between perceptions, resource access, and comfort. No significant differences were observed across demographic variables; while this does not establish equivalence, it suggests the course may be broadly accessible across participant groups. Qualitative findings, including participant reflections, highlighted the transformative impact of the course, with educators reporting a shift from skepticism to enthusiasm. The course's modular design, grounded in best practices for professional learning, was well-received and scalable. Recommendations include expanding the course to a larger and more mixed sample, integrating AI training into preservice teacher education, and updating content regularly to reflect the rapidly evolving AI landscape. This research demonstrates that thoughtfully designed, flexible professional development can build AI literacy and empower educators to adopt emerging technologies with confidence and purpose. As data collection is ongoing, these findings represent early trends that will inform future iterations and expanded implementation.

Keywords: AI; artificial intelligence; K–12; professional development; teacher preparation; teacher workload; teacher burnout

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The integration of artificial intelligence (AI) in K–12 education is more than a technological shift; it represents an opportunity to reimagine how teachers teach and how students learn (Luckin, 2025). As AI tools become increasingly prevalent across industries, their potential to enhance teaching and learning outcomes also grows. Students need to be prepared to be in a world where AI will play a central role in both professional and personal lives. As such, equipping them with the foundational knowledge and ethical awareness needed to understand and engage with AI technologies is essential.

Teachers are the frontline implementers of educational change, and their comfort, confidence, and competence are critical to the successful integration of new technologies, like AI, in classrooms (Shi et al., 2025). Currently, many educators express uncertainty about AI, including its applications, limitations, and ethical implications (Salloum, 2024). Along with these are barriers such as time constraints, a lack of targeted resources, and limited access to high-quality professional development that is both accessible and actionable (Roshan et al., 2024).

Historically, the integration of emerging technologies in schools, such as computers, the internet, and digital learning platforms, has followed a familiar pattern: early adoption by tech-savvy educators, followed by institutional support, and eventual broad adoption across educators (Yadegari et al., 2024). AI, however, presents new complexities due to rapid technological change, and its potential to disrupt existing pedagogical models demands a more deliberate and supported approach to professional learning. Teachers need more than just exposure to AI tools; they need sustained opportunities to develop AI literacy through hands-on application, ethical inquiry, support, and peer collaboration (Tan et al., 2025).

This is critical as policymakers and educational leaders begin calling for AI education at earlier grade levels. National initiatives, such as the AI4K12 framework, outline key concepts students should understand, including how AI systems work, the data they depend on, and the societal impacts they can generate (AI4K12, 2025). But for these efforts to be successful, K–12 educators must first be supported with practical, flexible training that demystifies AI and connects it meaningfully to classroom practice and provides recognition for their learning through innovative credentialing (Rajput & Sharma, 2025; Roshan et al., 2024).

To address this gap, an asynchronous professional development course for K–12 educators was developed. This paper introduces the course, which was designed to equip educators with foundational AI knowledge, promote ethical awareness, and provide practical strategies for classroom implementation. Developed collaboratively with librarians and grounded in instructional design best practices, the course is evidence-based, adaptable to meet various educator needs, and scalable across school systems. By evaluating the course's effectiveness through a mixed-methods research design, this study contributes to the growing body of knowledge on AI in education and offers a practical model for building AI literacy among educators at all levels of experience. This study presents findings from a pilot implementation of the course. As enrollment remains open and additional participants continue to engage with the program, the data reported here represent early trends that will inform iterative development and broader adoption.

Review of Related Literature

In order to design effective professional development for educators, it is essential to first understand the current landscape of AI in education. The following review synthesizes recent scholarship to highlight how AI is being used in educational settings, the unique challenges and opportunities it presents for K–12 contexts, and the growing emphasis on AI literacy for both teachers and students. By examining existing tools, professional learning frameworks, and implementation barriers, this section provides the foundation for understanding the need for targeted, flexible training models, such as the asynchronous course examined in this study.

AI in K–12 Education and Teacher Professional Development

AI has played a significant role in the digitalization of society (Cooper, 2023). The rapid evolution of AI technology in recent times has influenced individuals' productivity, and many now view AI as a force driving the fourth industrial revolution, with the potential to initiate transformative change in education through personalized training, adaptive curricula, and productive administrative processes (Alawneh et al., 2024; Zhai et al., 2021).

Over the past decade, there has been a significant shift towards data-driven machine learning (ML) techniques, which have outperformed traditional programming and rule-based AI methods across different domains (Darwiche, 2018). Rule-based refers to systems that rely on programmed, pre-established rules and logic, often implemented through if-then statements, regular expressions, and structured look-up tables, rather than learning patterns from data (Pappula & Rusum, 2024). This broader evolution from rule-derived approaches to adaptive ML systems has prompted educators to reassess instructional goals and pedagogical approaches (Pears et al., 2021; Shapiro & Fiebrink, 2019). In education, AI, commonly referred to as AIEd, encompasses technologies such as chatbots, automated grading systems, intelligent tutoring systems, and platforms designed to predict student performance, all of which are intended to enhance and support the educational process (Chiu et al., 2024).

Generative Artificial Intelligence (GenAI), for example, powered by Large Language Models (LLMs) such as ChatGPT, impacts teaching and learning by effectively generating responses to specific tasks (Magrill, 2024). Since OpenAI's public release of ChatGPT in November 2022, the educational landscape has experienced a rapid increase in AI adoption (OpenAI, 2022). Surveys from the 2024–2025 school year indicate that approximately 85% of teachers and 86% of students report using AI tools; however, only 48% of teachers have engaged in formal professional development on integrating AI into the classroom (Vilcarino & Langreo, 2025). This gap underscores the urgent need for targeted professional development to equip educators with the knowledge and ethical frameworks required for effective AI integration.

AI is increasingly integrated across four key areas of education: teaching, learning, assessment, and administration (Chiu et al., 2024). Researchers have adapted modeling and machine learning techniques from the business sector to enhance educational decision-making, including early alert systems to prevent dropout, visualization systems to track learning progress, recommender systems to personalize instruction, and adaptive systems that tailor content to learner needs (Allensworth, 2013; Marshall, 2022; Nistor et al., 2015; Wolff et al.,

2013). These systems also leverage learner-behavior data to predict grades, recommend remedial actions, and link performance with future academic or employment opportunities (Berendt et al., 2020).

Beyond these system-level applications, AI is transforming how teachers and students interact with content in the classroom. For example, platforms like Google's Teachable Machine help students train simple models using labeled images or sounds, which helps them grasp foundational ideas such as training data (Vartiaien et al., 2020). Widely used K–12 tools like Google's Teachable Machine, IBM's Machine Learning for Kids, and Wolfram's ML for Middle Schoolers reflect educational technology's "low floor, high ceiling, wide walls" principle, promoting accessibility and adaptability (Pope, 2024, p. 105). Robotics tools like Bee-Bots and LEGO Mindstorms foster algorithmic thinking and problem-solving through iterative design and coding (Kandlhofer et al., 2016). Programming environments (e.g., Scratch extensions), along with *k*-means clustering activities, provide interactive simulations that facilitate the exploration of grouping and classification concepts. These practical experiences help deepen understanding of how AI systems generalize from data (Dhariwal & Dhariwal, 2020; Wan et al., 2020). Personalized platforms such as Knewton and Edmodo adapt learning materials to individual needs, while generative tools like ChatGPT provide real-time feedback that supports reflection and improvement (Chiu, 2024; Chounta et al., 2022; Kohnke et al., 2023). AI-powered dashboards further enable teachers to identify learning gaps, adjust instruction, and monitor progress (Holstein et al., 2018; van Leeuwen & Rummel, 2020). Together, these applications illustrate how AI supports interactive, differentiated, and authentic learning experiences that mirror real-world AI practices.

At the same time, researchers have emphasized the growing need for AI literacy among educators and students (Dai et al., 2020; Taguma et al., 2018; Touretzky et al., 2019). K–12 students must understand AI concepts, applications, and ethics to effectively engage with the technology (Kandlhofer et al., 2016; Pedro et al., 2019). Strengthening educators' knowledge and confidence through such professional development initiatives is foundational for cultivating AI literacy among students, as teachers' own understanding directly shapes how AI concepts are introduced and integrated in K–12 classrooms. Researchers have emphasized the need for formal K–12 education to prioritize AI literacy, teaching students to engage with AI critically (Zimmerman, 2018), with particular emphasis on three key domains: AI concepts, AI applications, and AI ethics and safety (Wong et al., 2020). However, survey research from October 2024 found that far fewer than half of colleges and schools of education offered coursework on AI integration or embedded this information in existing courses, fewer than two-thirds had AI policies of their own, and much of the training that did exist focused on preventing student cheating rather than improving teacher practice (Weiner et al., 2024).

Guidance on how to approach AI classroom integration does exist for teachers. The AI4K12 research community has released a set of Five Big AI Ideas, which they believe should be included in the K–12 curriculum (AI4K12, 2025). The AI4K12 framework, developed by the Association for the Advancement of Artificial Intelligence (AAAI), and now jointly sponsored by AAAI and the Computer Science Teachers Association (CSTA), provides a national structure for teaching AI concepts in schools (AI4K12, 2025). The Five Big AI Ideas, (1) perception, (2) representation and reasoning, (3) learning, (4) natural interaction, and (5) societal impact, cover

topics from how machines learn from data to the broader societal impacts of AI (Touretzky et al., 2019). The framework promotes AI literacy through conceptual understanding, ethical reflection, and engagement with technology. It has increasingly guided curriculum design and teacher professional development initiatives, offering educators a foundation for integrating AI concepts into classroom practice. Educators have started using AI technologies to address a variety of educational tasks, as demonstrated by the expanding academic conversations occurring at the intersection of AI and education's interdisciplinary fields (Feng & Law, 2021; Luckin & Holmes, 2016).

As schools begin to adopt AI tools, the effectiveness of these technologies ultimately depends on teachers' ability and confidence in using them. Research has increasingly shifted toward understanding how professional development can prepare educators for integrating AI. Studies in this area emphasize the importance of training that combines both technical knowledge and pedagogical application, enabling teachers to effectively integrate AI into instruction while upholding ethical classroom practices. Empirical research has demonstrated the positive impact of structured AI professional development for K–12 educators. For instance, Unal and Unal (2025) reported that a two-session AI workshop significantly reduced workload perceptions, increased prompt-writing self-efficacy, and mitigated key implementation barriers. Similarly, Sun et al. (2023) found that participation in an AI integration program enhanced teachers' self-efficacy and the incorporation of AI tools in lesson planning. These studies demonstrate how targeted professional development can enhance teachers' knowledge, refine their instructional skills, and increase their comfort and confidence with AI tools, while promoting positive shifts in perception toward classroom integration. However, few studies have examined how such outcomes can be achieved through asynchronous professional development, particularly in terms of teachers' access to AI resources. The present study builds on this literature by investigating how an asynchronous AI professional development course affects educators' comfort, perception, and access, key constructs identified in emerging research on AI literacy in K–12 education.

The constructs examined in this study, comfort, perception, familiarity, and access, are well established in the literature as important to educators' technology adoption. Teachers' comfort with technology influences their likelihood of adopting new technology (Bove & Conklin, 2019), while perceptions of AI's value shape their openness and willingness to integrate it into the classroom (Mundy et al., 2012). Familiarity with technology, whether through previous experience or professional development, increases confidence and reduces barriers (Jääskelä et al., 2017; Khlaif, 2018). Access to resources, including professional learning opportunities and support from the school, remains a significant factor affecting technology use in schools (Francom, 2020; Freeman et al., 2017). These four variables provide a useful framework for understanding how professional development can influence teachers' integration of AI into the classroom.

AI can transform education by offering personalized learning experiences tailored to each student's unique needs and interests (Haristiani, 2019). In K–12 settings, generative AI can enhance learning by promoting self-regulated learning (Kong & Yang, 2024). Additionally, AI can support teachers in designing learning activities, scaffolding strategies, and interpreting performance data (Chounta & Avouris, 2016; Pardo, 2018; Roll & Wylie, 2016). Demanding

workloads were a persistent issue for classroom teachers before the pandemic (Jennin et al., 2021) and were exacerbated during and following the crisis (Marshall & Pressley, 2024). A recent study found that teachers who used generative AI weekly saved up to six hours per week—the equivalent of six weeks per school year (Gallup Inc. & Walton Family Foundation, 2025). This matters because increased teacher workloads correlate with elevated levels of teacher stress (Bellibaş et al., 2024), lower morale (Marshall et al., 2024), and ultimately increased teacher attrition (Tompkins, 2023). Training teachers to effectively use AI in their classroom practice could improve each of these metrics.

To support teachers in delivering personalized education and boosting student outcomes, AI should be seen as a tool that enhances and complements their work and not as a replacement (Rukadikar & Khandelwal, 2023). From a middle school teacher's perspective, for example, AI can help provide individualized feedback and support to a classroom full of learners who are being introduced to new topics (Pörn et al., 2024). For K–12 students, maintaining engagement is important for fostering long-term enthusiasm for learning; teachers should create AI-assisted environments that promote exploration, curiosity, and interactive learning (Bozkurt & Sharma, 2023; Mogavi et al., 2024). As students increasingly interact with AI technologies, it is essential that they recognize AI, learn how its algorithms function, ethically apply these algorithms to solve relevant problems, and assess AI systems (Ali et al., 2019). To support the successful functioning of future society, teacher education must incorporate AI literacy, which is typically defined as a collection of skills that allow individuals to critically evaluate AI technologies, interact and collaborate effectively with AI, and use AI as a tool in various settings (Long & Magerko, 2020). As schools and educators navigate these complex opportunities and challenges, professional development emerges as a central mechanism for equipping teachers with the confidence, skills, and ethical frameworks required to use AI effectively. Given teachers' demanding schedules and varying levels of prior experience with educational technology, online and flexible professional learning formats are especially important.

Asynchronous Online Professional Development

Asynchronous online learning has become an essential model for educator professional development, offering flexibility, accessibility, and opportunities for educators to revisit content for continued reflection and ongoing learning (Picault, 2021). Unlike traditional face-to-face or synchronous online formats, asynchronous environments allow educators to engage with content and peers at their own pace, an advantage given the demanding workloads and schedules of teachers. Research on online learning demonstrates that asynchronous formats can foster deep engagement through reflective discussions, self-regulated learning, and the integration of new practices into teaching (Lin & Sun, 2024). In the context of AI integration, asynchronous professional development can further enhance educators' comfort and pedagogical strategies without the time pressures of synchronous participation.

While research highlights many advantages of professional development, it is not without challenges. Some studies have noted barriers related to technology access and feelings of isolation among participants. For instance, participation in online learning depends on consistent internet connectivity and access to digital tools, conditions that may not be universally available to educators (Mhlanga, 2024). Additionally, participants in asynchronous courses sometimes report a

sense of isolation due to limited real-time interaction with peers and instructors (Gillett-Swan, 2017). This can be mitigated by incorporating features that intentionally foster a sense of instructor social presence among learners in the course (Garrison et al., 1999; Love & Marshall, 2022; Marshall & Love, 2025). Recognizing these challenges, the present study builds upon existing research by examining how a purposefully designed asynchronous professional development course can support K–12 educators in developing knowledge, skills, and self-efficacy related to AI while intentionally addressing barriers to engagement and connection.

Innovative Credentialing and Recognition in K–12 Professional Development

As professional development evolves to meet the needs of educators, innovative credentialing systems such as digital badges and microcredentials have emerged as an increasingly popular form of recognition. Digital badges are visual credentials that signify the acquisition of specific skills or knowledge, verified by an issuing institution or organization. They are particularly well-suited to asynchronous and modular learning environments, offering a flexible way to validate competencies not typically captured through traditional certification (Gibson et al., 2015). In the context of AI professional development, digital badges provide immediate and motivating recognition for educators' learning, supporting engagement and reinforcing the value of microlearning. They also offer transparency through metadata, detailing the badge criteria, issuer, and associated competencies (Randall et al., 2013). This makes badges useful for showcasing skills to colleagues, school leaders, or broader professional networks, including potential employers (Carey & Stefaniak, 2018). This alignment between flexible training and visible recognition supports the broader movement toward competency-based professional learning, where educators are empowered to demonstrate growth in applied areas such as AI integration and digital literacy. While digital badges offer a promising way to recognize and incentivize educator learning, their implementation must be accompanied by systemic support to ensure access and meaningful use. Issues of access, training, and ethical adoption, particularly about AI tools, remain significant challenges for many districts. As such, credentialing innovations like digital badges should be viewed not merely as tokens of completion but as part of a sustained professional learning ecosystem that encourages reflective practice and continued engagement with emerging technologies.

Challenges in Integrating AI into K–12 Education

Integrating AI into K–12 education presents several challenges, including limited collaboration and support, varying entry-level skills, unequal access to resources, and differing perceptions of AI among educators. Despite growing interest in student-AI collaboration, meaningful implementation of such practices remains limited because few teachers have sufficient guidance or examples of effective classroom use (Kim et al., 2023). One of the primary reasons for this difficulty is that many K–12 teachers lack the necessary knowledge and experience to teach and use AI effectively. To integrate these emerging technologies, teachers must overcome significant learning challenges related to unfamiliar subjects and often require substantial support from coaches and curriculum specialists (Ottenbreit- Leftwich et al., 2023). A comprehensive report on K–12 educational platforms (Ferguson et al., 2016) revealed that "intelligent" educational tools are seldom consistently used in classrooms, with potential explanations pointing to insufficient investment in resources or inadequate teacher training

(Freeman et al., 2017). For teachers to feel comfortable implementing a new technology in the classroom, they need access to a support system, including training and resources. Beyond access to training and resources, individual factors such as teachers' beliefs, comfort, and prior experiences also shape whether and how they choose to adopt AI technologies in their classrooms. The asynchronous professional development course examined in this study primarily addresses the challenges of entry-level AI skills and educators' perceptions and comfort, while broader issues related to collaboration and access are acknowledged but remain outside the scope of this pilot study.

Adoption of AI tools by teachers is influenced by multiple interrelated factors (Nelson et al., 2025), including ethical concerns, comfort level, prior experience, and perceptions of value. Teachers' concerns about the ethical use of AI in education often center on issues of privacy and data security, such as the implications of inputting student work into AI for grading or feedback purposes (Filiz et al., 2025). Additionally, educators express concerns about the accuracy of AI-generated information and its potential to diminish students' creativity, effort, and critical thinking skills. Teachers' comfort with new technologies also affects their likelihood of adoption; those who feel more confident and are supported are more inclined to integrate emerging tools into their teaching (Bove & Conklin, 2019). Prior experience plays a similar role; teachers with experience using similar technologies reported greater comfort and readiness when incorporating new ones (Jääskelä et al., 2017; Khlaif, 2018). Moreover, teachers' perceptions of the usefulness and instructional value of AI influence their willingness to adopt it. Mundy et al. (2012) found that teachers who not only learned about the technology but also how to effectively integrate it into their instruction were significantly more likely to use it than those who received only conceptual exposure. Collectively, these findings highlight the importance of addressing ethical awareness, technological comfort, and experiential familiarity when designing professional development initiatives to support the integration of AI in K–12 education. Because teachers' readiness and confidence directly influence classroom innovation, professional learning opportunities must move away from basic technical training to include ongoing mentorship and ethical reflection (Mouta et al., 2025). Beyond individual factors such as comfort, ethics, and prior experience, broader elements, including teaching experience, school type, and institutional policies, also influence teachers' readiness to integrate AI tools into their classrooms.

Educators' comfort with AI and other emerging technologies is shaped by multiple contextual factors, including teaching experience, school size and type, and district technology policies. Research indicates that pre-service and early-career teachers often demonstrate a higher willingness to adopt new technologies, although their pedagogical approaches may be less developed. In contrast, more experienced teachers may show lower confidence in integrating new technologies, despite having stronger instructional expertise (Forkosh-Baruch et al., 2021; Liu et al., 2015). School characteristics can also affect technology adoption: smaller schools often report greater access and administrative support than larger districts, while very small schools may face unique infrastructure barriers (Francom, 2020). Additionally, school type (e.g., public, private, charter, magnet) can impact the availability of resources and professional learning opportunities (Flavin, 2016). Finally, district technology-accessibility policies play a significant role in shaping teachers' opportunities to engage with AI tools. Federal initiatives such as the *National Education Technology Plan* (U.S. Department of Education, Office of

Educational Technology, 2023) and recent AI integration guidelines (U.S. Department of Education, Office of Educational Technology, 2024; Executive Office of the President of the United States, 2025) emphasize closing digital access divides and expanding educator training. However, implementation remains largely dependent on local resources and leadership (Patrick et al., 2021). Demographic and contextual factors are important in understanding the variability in teachers' comfort and readiness to use AI.

Since teachers play a pivotal role in implementing new pedagogical innovations in the classroom, successfully integrating AI concepts into K–12 education requires an AI-focused curriculum, suitable teaching resources, and adequate teacher preparation (Lindner & Berges, 2020). However, AI remains a new and unfamiliar subject for most teachers, who often complain about AI concepts and their functions. This is primarily due to their lack of experience and familiarity with the subject (Ottenbreit-Leftwich, 2023; Vazhayil, 2019). Addressing teachers' concerns about their limited knowledge of AI is critical. As AI skills rapidly evolve into essential life skills, schools will play a key role in fostering them. Therefore, comprehensive and intensive teacher training in AI is necessary to ensure effective instruction and the development of AI competencies (Lindner & Berges, 2020).

Conceptual Framework

This study is grounded in the Technology Acceptance Model (TAM), originally proposed by Davis (1985), which has undergone three iterations. The first iteration, TAM1, says that individuals' adoption of a technology is primarily shaped by perceived usefulness and perceived ease of use, which together influences attitudes and behavioral intention to use a tool. Building on this, TAM2 added social influence and cognitive instrumental factors that further explain perceived usefulness (Venkatesh & Davis, 2000), while TAM3 extended the model by specifying additional determinants of perceived ease of use, including output quality, job relevance, and result demonstrability (Venkatesh & Bala, 2008). Because AI adoption in K–12 settings depends on educators' beliefs about usefulness, ease, and contextual supports, TAM provides an appropriate lens for interpreting changes in teachers' comfort, perceptions, familiarity, and access following asynchronous professional development.

Methods

Guided by the Technology Acceptance Model, this study employed a concurrent mixed-methods design to evaluate the impact of an asynchronous professional development course aimed at building K–12 educators' self-perceived knowledge, comfort, and practical capacity to use AI in educational settings, using a mixed-methods approach to analyze data collected from pre- and post-course surveys (Creswell et al., 2011). Quantitative and qualitative data were analyzed together through a triangulated mixed-methods approach, allowing statistical results on comfort, perception, and familiarity to be interpreted alongside participants' reflections, lesson plans, and peer discussions for a more comprehensive understanding of the course's impact. This work was guided by the following questions:

1. How does participation in an asynchronous professional development course impact educators' overall engagement with artificial intelligence in education?
    a. How does the course affect educators' comfort with using AI in their professional practice?

   b. How does the course influence educators' perception of the value and role of AI in education?
   c. How does the course impact educators' access to and awareness of AI-related resources?
2. How does participation in the course influence educators' familiarity with AI tools and their potential classroom applications?
3. How does participation in the asynchronous professional-development course influence educators' openness to learning about AI and their post-course comfort, and do these outcomes vary by demographic factors (e.g., role, experience, or school type)?
4. What evidence exists of educators' application of AI in practice following the course, and what does this usage reveal about the transfer of learning from professional development to classroom practice?

Both quantitative and qualitative data were collected between November 2024 and April 2025. Thirty participants completed both the pre- and post-course surveys with matching identifiers, allowing for paired statistical analysis. In addition to survey results, participants' reflections, lesson plans, and discussion responses were collected to provide deeper insight into the course's effects. This study specifically examined how participation in an asynchronous professional development course improved educators' knowledge and skills related to AI integration, as measured through self-perception surveys administered before and after the course. To provide context for the study, it is important to describe the design and structure of the asynchronous professional development course that served as the intervention.

Course Design and Development

The asynchronous AI course was developed by an instructional design team within a university-based teaching and learning center that specializes in developing online professional development and academic courses. The development process was informed by a collaboration with a state librarians' association, which provided input on educators' needs and the types of AI training most relevant to K–12 contexts. This collaboration began during a pre-conference workshop in February 2024. This workshop brought together educational librarians who support K–12 teachers and technical systems. Through structured discussion and feedback, participants identified key gaps in AI understanding and outlined the types of training most needed to support widespread AI adoption in schools. These conversations highlighted varying levels of familiarity with AI concepts among educators, limited resources, and the necessity of a flexible training model that honors educators' time constraints.

Insights from this session directly shaped the development of a modular, research-aligned course tailored to K–12 educators. The workshop participants emphasized the need for an asynchronous format that allowed educators to engage at their own pace while offering practical tools, scenarios, and opportunities for reflection. The finalized course launched in November 2024 after a pilot at a state educational technology conference in June 2024.

The course includes eight modules: an introductory module, six content modules, and a concluding reflection module. The six core content modules were designed around themes that emerged from workshop data and research:

1. An overview of AI in education

2. Safety and ethical considerations
3. Information literacy and critical thinking
4. Utilizing AI for teaching and administration
5. Exploring AI tools for student learning
6. Assessment and evaluation

Each module follows a consistent structure: an opening overview, an instructional video featuring AI-generated personas, interactive readings, visuals, classroom scenarios, and practice opportunities. The personas—which include a fictional principal, librarian, two teachers, and a counselor—guide participants through the content in the context of a fictional K–12 school called the Innovation Academy. These characters were created to simulate peer dialogue and make complex topics more accessible.

Participants were placed in discussion forums based on grade level (e.g., PreK, elementary, middle, high school, special populations) to facilitate peer learning and shared lesson planning. Each module included hands-on activities, classroom implementation tasks, and reflection prompts. Participants earned microcredentials after each module and received a printable certificate and a digital "AI Educator Extraordinaire" badge upon course completion. This design supports professional learning best practices such as active engagement, sustained support, and direct application (Darling-Hammond et al., 2017; Guskey, 2002).

The course content was informed by national AI and computer science frameworks (e.g., AI4K12), legislative guidelines, and current scholarship in AI ethics and digital literacy. The development team prioritized accessibility, flexibility, and a clear connection to the classroom application. While the AI4K12 framework served as a curricular design guide for selecting AI-related concepts within the professional development course, it was not used as the theoretical framework for this study. Instead, the research is grounded in teacher professional learning, emphasizing how structured professional development influences educators' knowledge, comfort, and applications of emerging technologies.

Participants and Data Collection

Thirty participants completed both pre- and post-course surveys between November 2024 and April 2025 with matching identifiers, forming the initial sample for this pilot study. As the asynchronous professional development course remains open to new participants, these findings reflect data from the first cohort of teachers. Participants included current K–12 teachers (n = 11), preservice teachers (n = 8), and other educational professionals (n = 11), including administrators and homeschool educators. Although administrators are not classroom teachers, they were intentionally included in the professional development course because they support and oversee the integration of instructional technology within their schools. Including administrators alongside teachers ensured that both groups received consistent information about AI tools, ethics, and implementation strategies, promoting alignment between classroom practice and institutional decision-making. Of the 30 participants, 19 identified as female, 10 as male, and one selected "self-describe," though this response was excluded from gender-based statistical comparisons for privacy considerations.

Demographic information was gathered through the pre-course survey. The majority of participants held a master's degree (n = 13), while others reported having a bachelor's (n = 5), associate's (n = 5), or a doctoral degree (n = 1); six participants preferred not to respond. Most participants identified as White or Caucasian (n = 26), with limited representation from other racial and ethnic backgrounds. Employment status varied: 16 participants were employed full-time, six part-time, and eight reported "other," which primarily included preservice teachers not yet working in K–12 settings. Participants represented a range of school types, including public schools (n = 11), virtual or online schools (n = 6), micro or hybrid schools (n = 1), and "other" (n = 12), which again included preservice teachers. Eleven participants reported working in Title I schools. The participants had an average age of 27 years (M= 27.33; SD = 10.49), with notable variation across groups: K–12 teachers averaged 33.91 years (*SD* = 11.35), preservice teachers averaged 20.63 years (*SD* = 2.45), and other participants averaged 25.64 years (*SD* = 9.95). Among current K–12 teachers, the average number of years teaching was 9.36 (*SD* = 9.82).

In addition to quantitative survey data, qualitative data were collected through participants' written reflections, lesson plan submissions, and peer feedback discussions completed within the asynchronous course platform. Participants were encouraged to apply course concepts by designing AI-integrated lesson plans and commenting on peers' submissions to foster collaborative reflection and idea exchange. These qualitative activities provided insight into educators' evolving comfort, perceptions, and strategies for implementing AI in educational settings.

Example prompts included: "What additional steps might you take to teach your students to critically evaluate AI-generated information themselves?" and "How can K–12 teachers effectively integrate AI tools into the classroom while maintaining the crucial elements of human interaction and creativity in education?" These questions were designed to encourage reflection on both the opportunities and challenges of AI integration, connecting directly to the constructs of comfort, perception, and access explored in the study.

Survey Instrumentation

Pre- and post-course surveys were developed by the university's teaching and learning center to evaluate the effectiveness of an AI-focused professional development course for K–12 educators. They were designed to measure changes in participants' self-perceived AI-related knowledge, self-reported skills for classroom integration, perceptions, comfort levels, and access to AI-related resources using structured, closed-ended items. The goal was to capture measurable shifts in the key areas of AI integration in education through reliable, standardized data collection.

Both surveys incorporated Likert-type scales and multiple-choice descriptive questions. Items were grouped into several key constructs aligned with the course objectives: (1) familiarity with AI, which served as an indicator of participants' AI-related knowledge and understanding of AI concepts and tools; (2) openness to learning; (3) perceived value and relevance of AI in education and professional practice; (4) comfort using AI in various settings; and (5) access to and satisfaction with AI-related training resources. These constructs were informed by current

literature on educational technology adoption and teacher professional development, particularly in emerging technology contexts (Nazaretsky et al, 2022).

Participants rated their familiarity with AI and their willingness to learn about it on a 10-point scale ranging from 1 ("not familiar/open") to 10 ("extremely familiar/open). Perceptions of AI's value were measured using a 6-point Likert scale, where 1 indicated *strongly disagree*, and 6 indicated *strongly agree.* Example statements included "AI could enhance my productivity" and "AI technologies will affect my career in the next year." Comfort with AI was evaluated through a series of items assessing comfort levels in five areas: daily use, professional responsibilities, instructional applications, workplace integration, and general proficiency. Each was rated on a 6-point scale where a 1 indicated *very uncomfortable*, and a 6 indicated *very comfortable*, with an additional "not applicable" option to accommodate varying job roles.

To assess access to and engagement with training, participants responded to statements addressing the availability, clarity, and variety of AI training materials, as well as their confidence in seeking out such resources. Additional multiple-choice items captured participants' preferred methods for learning about AI (e.g., social media, websites, colleagues), frequency of engaging in AI-related training, and perceived barriers to implementation, such as cost, complexity, or lack of institutional support. These data points offered insights into the professional development courses surrounding AI adoption in K–12 settings.

The post-course survey retained all core constructs from the pre-survey to enable comparative analysis and added items specific to the course experience. These included measures of satisfaction, perceived relevance of course materials, increased confidence in using AI, and likelihood of integrating AI into future teaching or professional practice. All survey items were reviewed by subject matter experts in instructional design and educational technology to ensure content validity. To preserve anonymity while allowing for pre-post data matching, participants generated a unique identifier, typically a combination of their birthdate and street number digits, to use consistently for both surveys.

To evaluate internal consistency across the measured constructs, Cronbach's alpha was calculated for each construct, with the pre- and posttest combined for each construct. The resulting alphas indicated strong internal consistency for comfort ($\alpha = .818$) and access to resources ($\alpha = .876$). For perception, three incomplete cases were removed that did not complete all the perception questions, and the resulting alpha indicated strong internal consistency ($\alpha = .761$). This suggests stable construct measurement over the course duration.

Overall, the pre- and post-surveys provided a reliable and replicable framework for assessing changes in educators' readiness to engage with AI. Reliability was strengthened through consistent administration of identical items at both time points, careful construct alignment with course objectives and established technology-adoption research, and verification of internal consistency using Cronbach's alpha across the combined pre/post dataset. The use of standardized Likert-type, matrix, and 10-point rating scales supported replicability by enabling straightforward reuse of the instrument and comparison across groups. Because these measures reflect self-perception, complementary qualitative data were gathered separately through in-course discussions and participant reflections to triangulate findings and add depth. These

qualitative artifacts served as practical demonstrations of evolving understanding and confidence, allowing the research team to compare participants' reported growth with evidence of transfer into teaching. The following constructs formed the basis of the survey and guided the analysis of changes observed between the pre- and post-course measures.

Key Constructs and Measures

This study examined four primary constructs: comfort, perception, familiarity, and access to AI resources. Each construct was operationalized through items in the pre- and post-course surveys designed to assess changes in educators' confidence, attitudes, and resource awareness. Comfort refers to an educator's self-reported level of ease or confidence when using AI tools in education. Perception is defined as an educator's attitudes, beliefs, or opinions regarding the value, relevance, and potential impact of AI in education. Familiarity measures the degree to which educators understand AI concepts, tools, and classroom applications. Access to AI-related resources includes both the availability and usability of tools, training, and support necessary for effective AI use. While the professional development course itself is considered a resource, access may still be limited by external factors such as paywalls (e.g., requiring a subscription for tools like ChatGPT), institutional policies that restrict or ban AI tools, or lack of infrastructure or support within a school or district.

Data Analysis

Quantitative data were analyzed descriptively first. To determine whether statistically significant changes existed in participants' comfort with AI, perception of AI, familiarity with AI tools, and access to AI-related resources, paired-sample *t*-tests were conducted. Changes were considered significant at the $p < .05$ level, and effect sizes (d) were calculated to assess the magnitude of these changes. In addition, Spearman's rho correlations were conducted due to the non-normal distribution of some variables. These analyses were used to explore relationships between key constructs, particularly between participants' perceptions of AI and their comfort levels, as well as between resource access and comfort. To investigate potential differences in outcomes based on participant characteristics, independent-sample *t*-tests and factorial analysis of variance (ANOVA) tests were conducted to examine variables such as gender, school type, Title I status, and employment role. SPSS version 30 was used to analyze all quantitative data. Qualitative data were analyzed using ATLAS.ti version 25. Participant reflections, lesson plans, and peer feedback posts were analyzed using inductive coding to identify recurring themes in participants' experiences with AI tools and pedagogical applications. Two researchers independently coded a subset of responses and reached consensus through discussion. Triangulation was achieved by comparing qualitative themes with quantitative results from the pre- and post-course surveys, examining how participants' reported comfort, familiarity, and perceptions aligned with their written reflections and lesson plan evidence. This mixed-methods approach strengthened the credibility of findings by linking educators' self-perceptions with authentic demonstrations of knowledge and skills development.

Validity and Rigor

Validity and rigor were addressed through design and analytic strategies. First, internal validity was supported by using a paired pre/post-test survey design with matching identifiers, which allowed each participant to serve as their own comparison. Second, construct validity was strengthened by aligning survey items to clearly defined constructs grounded in prior technology-adoption and AI professional development, and by confirming internal consistency through Cronbach's alpha for each construct. Third, methodological triangulation increased credibility by comparing quantitative change scores with qualitative evidence from reflections, lesson plans, and peer discussion posts. Despite these strategies, the small pilot sample limits external validity and may overrepresent early adopters who were already open to AI, creating potential selection bias. This limitation is acknowledged in the discussion and recommendations, and future studies will incorporate larger samples.

Results

The findings are presented in alignment with the four research questions. Quantitative results address RQs 1-3 using pre- and post-survey comparisons, correlations, and demographic analyses. Qualitative findings address RQ4 by summarizing patterns in participants' reflections, lesson plans, and peer discussion posts.

RQ1. How does participation in an asynchronous professional development course impact educators' overall engagement with artificial intelligence in education?

Paired-sample *t*-tests showed statistically significant improvements across all three core constructs: comfort with AI, perceptions of AI, and access to AI resources. See Table 1 for means, *p*-values, and effect sizes.

Table 1

Effect of Course Completion on Key Constructs

Construct	Pre-Test Mean	Post-Test Mean	*p*-value	Cohen's *d*
Comfort with AI	3.320	4.824	<.001**	1.07
Perception of AI	5.447	6.087	.011*	.50
Resource Access	3.667	4.706	.003**	.60

Notes. Scale is from 1–7 for each construct.
$p < .01$ = significant at the .01 level (**), $p < .05$ = significant at the .05 level (*).

RQ1a. How does the course affect educators' comfort with using AI in their professional practice?

Participants' comfort with AI increased from a pre-test mean of 3.32 to a post-test mean of 4.82 ($p < .001$, $d = 1.07$), indicating a large effect**.** These results suggest that the course substantially strengthened educators' confidence and ease in using AI tools for professional and instructional purposes.

RQ1b. How does the course influence educators' perception of the value and role of AI in education?

Perceptions of AI improved from 5.45 to 6.09 ($p = .011$, $d = 0.50$), indicating significantly more positive perceptions following the course. Participants left the course with stronger beliefs about AI's usefulness and relevance in K–12 settings.

RQ1c. How does participation in the course influence educators' familiarity with AI tools and their potential classroom applications?

Access to AI-related resources rose from 3.67 to 4.71 ($p = .003$, $d = 0.60$), showing significant improvement in access to and awareness of AI resources. This suggests the course helped educators identify, locate, and feel more capable of using AI-related tools and support.

RQ2. How does participation in the course influence educators' familiarity with AI tools and their potential classroom applications?

Participants reported a significant increase in familiarity with AI, moving from a pre-test mean of 5.20 to 7.17 post-test ($p < .001$, $d = 0.74$). This indicates that participants perceived themselves as substantially more knowledgeable about AI tools and how these tools could be applied in educational contexts following the course.

Table 2

Significance of Course on Familiarity

Question	Pre-Test Mean	Post-Test Mean	*p*-value	Cohen's *d*
Familiarity with AI	5.200	7.167	<.001**	.74

Note. Scale is from 1-10 for each question.
p < .01 = significant at the .01 level (**), p < .05 = significant at the .05 level (*).

RQ3. How does participation in the asynchronous professional development course influence educators' openness to learning about AI and their post-course comfort, and do these outcomes vary by demographic factors?

Openness to learning about AI showed no statistically significant change (7.83 to 7.97, $p = .762$), likely due to a ceiling effect, as participants already reported high levels of openness before the course. See Table 3 for means, *p*-values, and effect sizes.

Table 3

Significance of Course on Openness to Learn

Question	Pre-Test Mean	Post-Test Mean	*p*-value	Cohen's *d*
Openness to Learn	7.833	7.967	.762	.06

Note. Scale is from 1-10 for each question.
p < .01 = significant at the .01 level (**), p < .05 = significant at the .05 level (*).

Relationships Among Openness, Comfort, Perception, and Access (Exploratory)

To better understand how key constructs relate to educators' willingness to engage with AI, correlations were examined. Statistically significant correlations were found between

participants' comfort with AI and both perception of AI and access to AI resources. At pre-test, comfort was positively correlated with perception (ρ = .538, p = .002) and with access (ρ = .549, p = .002). These relationships remained significant at post-test: perception (ρ = .446, p = .014) and access (ρ = .525, p = .003). These findings suggest that favorable attitudes toward AI and awareness of resources are strongly linked with comfort in applying AI.

Demographic Differences in Post-course Comfort

Independent-sample *t*-tests revealed no significant differences in comfort with AI based on gender (p = .395, d = .10), education level (p = .479, d = .30), or Title I status (p = .793, d = .10). Education level was operationalized as having a graduate degree (i.e., master's, doctorate, professional) or not. See Table 4 for results.

Table 4

Independent Samples t-Test Results: Gender and Title I Status

Variable	Group Comparison	*t*(df)	*p*-value	Cohen's *d*
Gender	Male vs. Female	-.864(27)	.395	.10
Education Level	Grad Degree vs. No	-.720(22)	.479	.30
Title I Status	Yes vs. No	.264(28)	.793	.10

Note. Given the small sample sizes, Mann-Whitney U tests were also conducted for each of the variables, yielding similar results.

Spearman correlations with continuous variables also revealed no significant associations. Age (ρ = .007, p = .971) and years of teaching (ρ = –.200, p = .308 and comfort with AI did not reach statistical significance. See Table 5 for results.

Table 5

Comfort with AI by Age and Years of Teaching

Variable	Spearman's ρ	*p*-value	N
Age (in years)	.007	.971	30
Years of Teaching	-.200	.308	28

These results indicate that demographic variables had little to no effect on participants' post-course confidence using AI, suggesting the course's effectiveness was consistent across professional contexts.

RQ4. What evidence exists of educators' application of AI in practice following the course, and what does this usage reveal about the transfer of learning?

Qualitative analysis of participants' end-of-course reflections, lesson plan submissions, and peer discussion responses revealed clear evidence of transfer from professional development into practice-oriented thinking. Because reflection and discussion prompts varied across

modules, participants did not respond to a single uniform set of questions; therefore, findings are reported thematically rather than quantified by frequency. Across data sources, participants consistently described applying course concepts to instructional planning, student learning supports, ethical literacy, and administrative work. Many participants reported using AI tools to assist with lesson design and instructional preparation, noting that platforms such as Canva, Edpuzzle, and Lumio could streamline the development of visually engaging or interactive class materials. These reflections often emphasized that AI-supported design reduced planning time while expanding the variety of instructional resources educators felt able to create.

In addition to lesson design, participants frequently discussed plans for using AI to personalize or scaffold student learning. Teachers described AI as a tool for generating differentiated activities, supporting individualized feedback, or adapting content to meet various learner needs. Several reflections linked these uses of AI in instruction to workload relief, suggesting that time saved through the use of AI could be used with students. Further, a strong emphasis emerged around ethical AI use and critical thinking. Teachers described strategies for verifying outputs generated by AI, identifying potential bias, and ensuring accuracy, and many teachers extended these ideas into how they could teach students how to use AI. Educators outlined plans to explicitly teach learners how to evaluate AI-generated information, check credibility, and reflect on responsible use.

Finally, participants recognized AI as a support tool beyond simply using it in the classroom. Many participants described administrative uses such as summarizing information, drafting communications, organizing tasks, or automating repetitive professional responsibilities. These applications of AI were often framed as realistic, near-term uses that could reduce burnout. Together, these patterns show that educators moved from an overall awareness of AI toward specific, practice-oriented applications. Their reflections and lesson plans demonstrate that course participation not only supported changes in mindset but also the development of strategies for integrating AI into K–12 education.

Summary of Key Findings

This pilot study explored the impact of an asynchronous professional development course on K–12 educators' engagement with AI in education. Participation in the course led to statistically significant improvements in educators' comfort with AI, perceptions of its value, and awareness of AI-related resources, with medium to large effect sizes. Educators' familiarity with AI increased significantly, while openness to learning about AI remained stable, likely due to already high pre-course scores. Demographic variables, including gender, years of teaching, and whether a teacher taught at a Title I school, were not significantly associated with post-course comfort with AI, suggesting the course was broadly effective across participant profiles. Evidence from participant reflections revealed a wide range of practical applications, from instructional design and student engagement to time-saving strategies and critical evaluation of AI outputs. Many educators developed lesson plans, instructional activities, and classroom policies that incorporated AI in thoughtful and pedagogically sound ways. Overall, the course positively influenced both mindset and practice, supporting educators in building the knowledge, confidence, and capacity needed to integrate AI responsibly in educational settings.

Discussion

The results of this pilot study provide preliminary evidence that an asynchronous, modular professional development course can significantly enhance educators' self-perceived knowledge and comfort with AI, positively influence their perceptions, and increase their awareness of available AI resources. These outcomes align with those of Lindner and Berges (2020), who emphasize the importance of targeted professional development for effectively integrating AI into educational practice. Gains were found across all three key constructs: comfort with AI, perceptions of AI, and access to resources. These findings suggest that the course effectively addressed barriers often associated with technology adoption in K–12 environments, including unfamiliarity, limited access, and skepticism. This supports the work of Nazaretsky et al. (2022), who identify these constructs as central components in AI-focused educator training programs. These patterns are also consistent with TAM, which states that perceived usefulness and perceived ease of use are important factors in educators' willingness to adopt new technologies (Davis, 1985; Venkatesh & Davis, 2000; Venkatesh & Bala, 2008). In this study, perception aligns with perceived usefulness, comfort aligns with perceived ease of use, and access reflects facilitating opportunities that support adoption.

One of the strongest insights emerged in the relationship between participants' perceptions of AI and their comfort levels. Correlational analyses found moderate to strong positive relationships at both pre- and post-test, indicating that those who perceived AI more favorably also reported greater comfort using it. This relationship held after course completion, suggesting that the course not only improved skills but also shifted attitudes. Similarly, participants who were more aware of AI resources were significantly more comfortable using AI, both before and after the course. These findings reinforce the importance of providing teachers with both practical resources and opportunities to build confidence, aligning with Long and Magerko (2020), who argue that for educators to effectively integrate AI, they must first be equipped with the necessary skills and support. An important caveat to consider is that the pilot findings may reflect the attitudes of *early adopters*—those more open to exploring emerging technologies in the first place.

Interestingly, the study found no statistically significant differences in comfort with AI based on demographic factors such as age, gender, race, education level, school type, or employment status. While these results do not provide statistical evidence of equivalence, the absence of significant differences suggests that the course may have been broadly accessible and relevant across participant groups. This assumption should be interpreted cautiously, as the small and relatively homogenous sample may have limited the detection of group-level variation. The lack of demographic differences may also reflect a common trait among participants: they were likely early adopters of educational technology, already predisposed to engaging with innovative tools such as AI.

Qualitative findings also demonstrated how educators translated course learning into practice. Across reflections, lesson plan submissions, and peer discussions, participants described concrete applications of AI for classroom planning, student support, and ethical AI literacy. Several educators reported shifting from uncertainty or limited awareness of AI use to identifying specific strategies such as generating learning supports, designing AI-integrated

activities, and teaching students how to think critically with AI. Participants also emphasized the value of the asynchronous format, peer learning, and scenario-based design in lowering intimidation and increasing confidence. These themes suggest that gains in comfort and perception were connected to emerging practical capacity, supporting the argument that effective professional development must include both conceptual foundations and applied experiences (Zimmerman, 2018).

The findings outlined here are promising; however, it is worth noting that not all teachers in the U.S. are finding AI to be as useful. Phi Delta Kappan's annual survey of teacher opinions found that teachers' acceptance of AI for tasks ranging from lesson planning to personalizing learning to student test prep fell from the 2024 survey to 2025 (Hendron, 2025). As previously noted, many teachers already experience elevated workloads. Any new tool they are asked to learn must demonstrate value—underscoring the need for effective training. As data collection continues, future analyses will provide a more comprehensive understanding of the course's long-term impact and scalability.

Limitations

There are several limitations that must be addressed in future studies. Among them is the small sample size, which limits the generalizability of the findings. Though meaningful correlations and statistical significance were achieved, future studies should include more robust samples. Additionally, future studies should intentionally recruit educators at varying stages of the technology adoption curve, including those categorized as *late adopters* or *laggards*, to better understand the course's impact across all educators. Finally, this pilot relied primarily on self-perception survey measures; although reflections and lesson plans provided supportive evidence of application, future work would benefit from additional performance-based or observational indicators.

Recommendations for Future Research

Longitudinal studies should follow participants after course completion to assess how AI integration evolves. Follow-up interviews or focus groups would allow for deeper insights into the specific instructional and administrative uses of AI and provide feedback for course refinement. Future studies should intentionally recruit educators at varying stages of the technology adoption curve, including those categorized as late adopters or laggards, to better understand the course's impact across all educators. Future work should also explore the impact of such professional development on student outcomes and ethical practices related to AI use in classrooms. For broader impact, findings should be disseminated beyond academic circles to reach district leaders, policymakers, teacher education programs, and professional learning providers. Doing so would help shape future professional development efforts not only for AI but for other emerging technologies such as virtual and augmented reality.

Conclusion

This pilot study demonstrates that targeted, well-designed professional development can significantly enhance educators' confidence and readiness to integrate AI into their classrooms. The asynchronous AI course offered not only knowledge acquisition but also practical tools,

real-world applications, and community engagement, factors that collectively contributed to its success. The consistent improvement in comfort, perception, and access across all demographic groups suggests that such programs can meet the needs of today's K–12 educators. This initiative serves as a model for supporting educators through the rapidly evolving landscape of educational technology. As AI tools continue to change educational environments, supporting teachers in adopting them responsibly and effectively is important, not only for instructional improvement but also to help reduce teacher burnout and promote retention. Through intentional course design and alignment with established principles of professional learning, the course supported the development of greater confidence and ethical awareness in the use of AI tools. These early findings offer valuable insight for future iterations of this specific course, as well as for the design of other AI professional development initiatives.

Ethics Board Statement

This research was approved as exempt by Auburn University's Institutional Review Board (approval # 24-948).

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