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

Moon-Heum Cho
Syracuse University

Ying Chen
Syracuse University

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

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

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

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

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

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

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

Theoretical Framework

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

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

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

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

Social Demographic Information

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

Value of AI Tools for Student Learning

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

Utility of AI Tools for Personal Academic Tasks

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

Self-Efficacy in Using AI Tools

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

Research Questions

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

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

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

Methods

Research Contexts and Participants

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

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

Measurements

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

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

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

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

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

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

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

Procedures

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

Results

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

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

Table 1

Mean and Standard Deviation of Study Variables

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

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

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

Table 2

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

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

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

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

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

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

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

Table 3

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

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

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

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

ID Students' Experiences, Perspectives, and Training Needs

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

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

Table 4

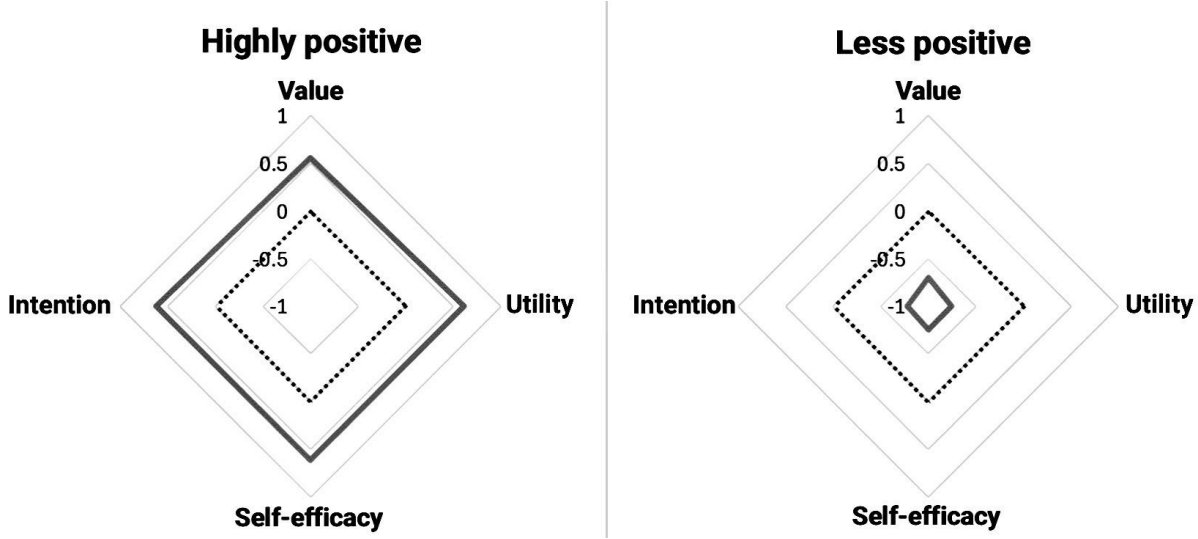
Descriptive Statistics for Two Perspective Clusters on AI (N = 74)

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

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

Figure 1

Profiles of ID Students' Perspectives on AI Tools



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

Content Analysis

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

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

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

Primary Uses of AI Tools for ID Assignments

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

Table 5

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

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

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

Perceptions of AI in ID

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

Table 6

ID Students' Perceptions of AI in Education by Cluster

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

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

Necessary Training to Learn AI Tools in ID

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

Table 7

Necessary Training to Learn AI Tools in ID

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

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

Discussion

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

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

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

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

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

Practical Guidance to Enhance ID Students' AI Literacy

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

Strengthen Personal Utilization of AI Tools Through Course Integration

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

Help Students Recognize AI's Value for Future Learners

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

Enhance Students' Self-Efficacy in Using AI Tools

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

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

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

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

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

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

Limitations

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

Declarations

Conflicts of Interest Statement

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

Data Availability Statements

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

References

Akgun, S., & Greenhow, C. (2022). Artificial intelligence in education: Addressing ethical challenges in K-12 settings. *AI and Ethics*, *2*(3), 431–440. https://doi.org/10.1007/s43681-021-00096-7

Al Omari, O., Alshammari, M., Al Jabri, W., Al Yahyaei, A., Aljohani, K. A., Sanad, H. M., Al-Jubouri, M. B., Bashayreh, I., Fawaz, M., ALBashtawy, M., Alkhawaldeh, A., Qaddumi, J., Shalaby, S. A., Abdallah, H. M., AbuSharour, L., Al Qadire, M., & Aljezawi, M. (2024). Demographic factors, knowledge, attitude and perception and their association with nursing students' intention to use artificial intelligence (AI): A multicentre survey across 10 Arab countries. *BMC Medical Education*, *24*(1), Article 1456. https://doi.org/10.1186/s12909-024-06452-5

Al-Maaitah, T. A., Alduneibat, K. A., Alshdaifat, S. M., Alsarayreh, R., Bani Ahmad, A. Y. A., & Hijazin, A. (2025). AI adoption, technological readiness, and AI usability in sustainability accounting education: The moderating role of academic integrity. *Heritage and Sustainable Development*, *7*(1), 611–628. https://doi.org/10.37868/hsd.v7i1.1176

An, X., Chai, C. S., Li, Y., Zhou, Y., Shen, X., Zheng, C., & Chen, M. (2023). Modeling English teachers' behavioral intention to use artificial intelligence in middle schools. *Education and Information Technologies, 28*(5), 5187–5208. https://doi.org/10.1007/s10639-022-11286-z

Anderson, S. E., Groulx, J. G., & Maninger, R. M. (2011). Relationships among preservice teachers' technology-related abilities, beliefs, and intentions to use technology in their future classrooms. *Journal of Educational Computing Research*, *45*(3), 321–338. https://doi.org/10.2190/EC.45.3.d

Bandura, A. (2006). Guide for constructing self-efficacy scales. In F. Pajares & T. Urdan (Eds.), *Self-efficacy beliefs of adolescents* (Vol. 5, pp. 307–337). Information Age Publishing.

Bolick, A. D., & da Silva, R. L. (2024). Exploring artificial intelligence tools and their potential Impact to ID workflows and organizational systems. *TechTrends*, *68*(1), 91–100. https://doi.org/10.1007/s11528-023-00894-2

Boyle, C. (2025). ChatGPT, Gemini, & Copilot: Using generative AI as a tool for information literacy instruction. *The Reference Librarian*, *66*(1–2), 13–29. https://doi.org/10.1080/02763877.2025.2465416

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, *20*(1), Article 43. https://doi.org/10.1186/s41239-023-00411-8

Chen, X., & Wu, D. (2024). Automatic generation of multimedia teaching materials based on generative AI: Taking Tang poetry as an example. *IEEE Transactions on Learning Technologies*, *17*, 1353–1366. https://doi.org/10.1109/TLT.2024.3378279

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Granić, A. (2022). Educational Technology Adoption: A systematic review. *Education and Information Technologies, 27*, 9725–9744. https://doi.org/10.1007/s10639-022-10951-7

Hong, J. W. (2022). I was born to love AI: The influence of social status on AI self-efficacy and intentions to use AI. *International Journal of Communication*, *16*, 172–191. https://ijoc.org/index.php/ijoc/article/view/17728

Hopson, S., Mildon, C., Hassard, K., Kubalek, C., Laverty, L., Urie, P., & Corte, D. D. (2025). Enhancing AI literacy in undergraduate pre-medical education through student associations: An educational intervention. *BMC Medical Education*, *25*(1), Article 999. https://doi.org/10.1186/s12909-025-07556-2

Lee, K. Y., Sheehan, L., Lee, K., & Chang, Y. (2021). The continuation and recommendation intention of artificial intelligence-based voice assistant systems (AIVAS): The influence of personal traits. *Internet Research*, *31*(5), 1899–1939. https://doi.org/10.1108/INTR-06-2020-0327

Lee, Y., & Lee, J. (2014). Enhancing pre-service teachers' self-efficacy beliefs for technology integration through lesson planning practice. *Computers & Education*, *73*, 121–128. https://doi.org/10.1016/j.compedu.2014.01.001

Lin, Y. S., Chen, S. Y., Tsai, C. W., & Lai, Y. H. (2021). Exploring computational thinking skills training through augmented reality and AIoT learning. *Frontiers in Psychology*, *12*, Article 640115. https://doi.org/10.3389/fpsyg.2021.640115

Luo, T., Muljana, P. S., Ren, X., & Young, D. (2025). Exploring IDers' utilization and perspectives on generative AI tools: A mixed methods study. *Educational Technology Research and Development*, *73*(2), 741–766. https://doi.org/10.1007/s11423-024-10437-y

Marín, Y. R., Caro, O. C., Rituay, A. M. C., Llanos, K. A. G., Perez, D. T., Bardales, E. S., Tuesta, J. N. A., & Santos, R. C. (2025). Ethical challenges associated with the use of artificial intelligence in university education. *Journal of Academic Ethics*, 23, 2443–2467. https://doi.org/10.1007/s10805-025-09660-w

McGehee, N. (2024). *Breaking barriers: A meta-analysis of educator acceptance of AI technology in education*. Michigan Virtual. https://michiganvirtual.org/research/publications/breaking-barriers-a-meta-analysis-of-educator-acceptance-of-ai-technology-in-education/

Moundridou, M., Matzakos, N., & Doukakis, S. (2024). Generative AI tools as educators' assistants: Designing and implementing inquiry-based lesson plans. *Computers and Educators: Artificial Intelligence*, *7.* Article 100277. https://doi.org/10.1016/j.caeai.2024.100277

Owan, V. J., Abang, K. B., Idika, D. O., Etta, E. O., & Bassey, B. A. (2023). *Exploring the potential of artificial intelligence tools in educational measurement and assessment*. *Eurasia Journal of Mathematics, Science and Technology Education, 19*(8), Article em2307. https://doi.org/10.29333/ejmste/13428

Park, E. G., Lim. S., & Cho, M.-H. (2026). College students' intention to use AI tools in academia. *International Journal of Emerging Technologies in Learning, 21*(1), 43–58. https://doi.org/10.3991/ijet.v21i01.58065

Park, Y., & Doo, M. Y. (2024). Role of AI in blended learning: A systematic literature review. *International Review of Research in Open and Distance Learning*, *25*(1), 164–196. https://doi.org/10.19173/irrodl.v25i1.7566

Parsons, B., & Curry, J. H. (2024). Can ChatGPT pass graduate-level ID assignments? Potential implications of artificial intelligence in education and a call to action. *TechTrends*, *68*(1), 67–78. https://doi.org/10.1007/s11528-023-00912-3

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education, 128*, 13–35. https://doi.org/10.1016/j.compedu.2018.09.009

Schreier, M. (2012). *Qualitative content analysis in practice*. (Vols. 1-0). SAGE Publications Ltd, https://doi.org/10.4135/9781529682571

Shao, C., Nah, S., Makady, H., & McNealy, J. (2025). Understanding user attitudes towards AI-enabled technologies: An integrated model of self-efficacy, TAM, and AI ethics. *International Journal of Human–Computer Interaction*, *41*(5), 3053–3065. https://doi.org/10.1080/10447318.2024.2331858

Shehata, A., Saleem, N., & Hamad, F. (2026). Exploring social sciences and humanities student perspectives on AI in higher education: A comprehensive study of usage, ethics, and future intentions. *Online Learning, 30*(1), 478–506. https://doi.org/10.24059/olj.v30i1.4989

Silapachote, P., & Srisuphab, A. (2017). Engineering courses on computational thinking through solving problems in artificial intelligence. *International Journal of Engineering Pedagogy*, *7*(3), 34–49. https://doi.org/10.3991/ijep.v7i3.6951

Teeroovengadum, V., Heeraman, N., & Jugurnath, B. (2017). Examining the antecedents of ICT adoption in education using an extended Technology Acceptance Model (TAM). *International Journal of Education and Development Using Information and Communication Technology*, *13*(3), 4–23. https://www.learntechlib.org/p/182155/

Trust, T., Whalen, J., & Mouza, C. (2023). Editorial: ChatGPT: Challenges, opportunities, and implications for teacher education. *Contemporary Issues in Technology and Teacher Education*, *23*(1), 1–23. https://citejournal.org/wp-content/uploads/2023/02/v23i1editorial1.pdf

Ursavaş, Ö. F., Yalçın, Y., İslamoğlu, H., Bakır-Yalçın, E., & Cukurova, M. (2025). Rethinking the importance of social norms in generative AI adoption: Investigating the acceptance and use of generative AI among higher education students. *International Journal of Educational Technology in Higher Education*, *22*(1), Article 38. https://doi.org/10.1186/s41239-025-00535-z

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Wang, L., & Li, W. (2024). The impact of AI usage on university students' willingness for autonomous learning. *Behavioral Sciences*, *14*(10), Article 956. https://doi.org/10.3390/bs14100956

Weng, X., Ye, H., Dai, Y., & Ng, O.-L. (2024). Integrating artificial intelligence and computational thinking in educational contexts: A systematic review of ID and student learning outcomes. *Journal of Educational Computing Research*, *62*(6), 1640–1670. https://doi.org/10.1177/07356331241248686

Woo, D. J., Wang, D., Yung, T., & Guo, K. (2024). Effects of a prompt engineering intervention on undergraduate students' AI self-efficacy, AI knowledge and prompt engineering ability: A mixed methods study. *arXiv.* https://doi.org/10.48550/arXiv.2408.07302

Yu, J. H., Chauhan, D., Iqbal, R. A., & Yeoh, E. (2025). Mapping academic perspectives on AI in education: Trends, challenges, and sentiments in educational research (2018–2024). *Educational Technology Research and Development*, *73*(1), 199–227. https://doi.org/10.1007/s11423-024-10425-2

Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. *Contemporary Educational Psychology*, *25*(1), 82–91. https://doi.org/10.1006/ceps.1999.1016