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Modeling the factors influencing technology students' intentions to use AI-driven virtual simulation apps in technical drafting and design education

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Abstract

The integration of artificial intelligence (AI) tools into educational settings is reshaping how students learn, create, and engage with digital technologies, particularly in fields such as technology and design education where virtual simulations and AI-assisted workflows are increasingly prevalent. Despite this momentum, student adoption of AI tools remains inconsistent, especially in developing regions where technological readiness and trust in emerging technologies vary widely. This study investigates factors influencing AI tool acceptance among 493 industrial technology students from a public university in Central Visayas, Philippines. Using structural equation modeling (SEM), the research examined the relationships among perceived usefulness, perceived ease of use, perceived risk, and behavioral intention to adopt AI-driven virtual simulation applications. Findings confirm that perceived usefulness and ease of use remain strong drivers of adoption intention, aligning with the Technology Acceptance Model (TAM). However, perceived risk demonstrated a significant negative influence on both perceptions and intentions, highlighting the impact of concerns related to data privacy, algorithmic transparency, and ethical implications of AI in design-oriented learning environments. Integrating perceived risk into TAM expands the explanatory power of the model in technical drafting and design education, offering a more comprehensive picture of how students evaluate and adopt AI-driven virtual simulation apps. This enriched perspective highlights the necessity for institutional strategies that build AI literacy, reinforce data governance mechanisms, and foster responsible engagement with emerging technologies. The results provide valuable insights for educators, curriculum designers, and policymakers working to advance AI-supported learning, particularly within resource-constrained and rapidly developing educational contexts.

Keywords Artificial intelligence adoption · AI-driven virtual apps · Higher education · Perceived risk · Structural equation modeling · Technology acceptance model · Technology and design education

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Introduction

In the rapidly evolving landscape of education, AI has begun to reshape learning environments, particularly in fields that require strong technical and visual spatial competencies such as those taught in technical drafting and design programs, including drafting technology, automotive design, civil technology, and interior design (Pinski and Benlian, 2024). In these disciplines, drafting serves as a fundamental design skill that supports ideation, visualization, and technical communication within the broader technical drafting and design process. AI-driven virtual simulation apps are increasingly integrated into these programs to enrich learning through dynamic, interactive, and personalized environments (Walter, 2024). These tools have shown potential to enhance conceptual understanding, foster creativity, and reduce learning challenges (Zailuddin et al., 2024). Despite these benefits, adoption remains uneven among technology students enrolled in technical drafting and design courses. Examining the factors that influence students' intentions to use AI-driven virtual simulation apps is therefore important for supporting meaningful integration within technology and design education.

AI-driven virtual simulation platforms such as Autodesk SketchBook, SketchUp, and Onshape are designed to support core tasks in technical drafting and design education, including 2D drafting, technical drawing, preliminary visualization, and 3D modeling (Shi, 2024). These applications use AI features such as real time error detection, automated feedback, predictive design suggestions, and adaptive learning functions (Gligorea et al., 2023). In technical drafting and design instruction, these capabilities strengthen project based learning, simulate professional workflows, facilitate remote collaboration, and enhance students proficiency in design processes (Anantrasirichai & Bull, 2021). These advantages align with the increasing emphasis on industry relevant and technology enhanced skill development in engineering and technology programs.

The integration of emerging technologies in education has often been analyzed using models such as the TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT). These frameworks emphasize constructs including perceived usefulness, perceived ease of use, performance expectancy, effort expectancy, social influence, and facilitating conditions in predicting technology adoption (Davis, 1989; Venkatesh et al., 2003). While these models have been applied in various educational settings, their use in understanding students' adoption of AI-driven virtual simulation tools specifically designed for technical drafting and design remains limited (Galimova et al., 2024; Yu et al., 2021).

Several gaps appear in the literature. First, research on technology adoption often centers on general academic tools rather than applications designed for discipline specific contexts such as technical drafting and design. Second, there is limited knowledge about how AI enhanced features including intelligent corrections and automated feedback influence students' perceptions of usefulness and ease of use. Third, although social influence and facilitating conditions are well established predictors of technology use, their importance in equipment intensive and collaborative technical drafting and design programs has not been sufficiently explored. Fourth, most existing studies rely on qualitative or descriptive approaches, resulting in limited quantitative evidence that validates the causal relationships underlying technology adoption. These gaps highlight the need for model driven empirical studies using SEM to examine the factors shaping technology students' intentions to use AI-driven virtual simulation apps.

Literature review

The integration of AI in educational settings, particularly in technical and vocational disciplines like design, drafting, automotive, and civil engineering, has received increasing scholarly attention (Gantalao et al., 2025). AI-driven virtual simulation apps are now becoming important tools for supporting skill development, conceptual understanding, and design proficiency through highly interactive digital environments. This literature review examines key areas relevant to the current study, including the role of AI in technical education, adoption of educational technologies in design fields, the evolution of digital design tools toward AI integration, and the factors influencing students' intentions to use AI-driven virtual simulation apps.

AI for skill development in technical drafting and design

AI has become more widely used in educational practices that require visual spatial reasoning, hands-on experimentation, and iterative problem solving—core characteristics of technical drafting and design (Xu & Ouyang, 2022; Yüksel et al., 2022). AI-enabled applications use machine learning, pattern recognition, and data-driven feedback mechanisms to simulate real design tasks in a controlled digital setting (Kökver et al., 2024). These tools provide automated feedback, highlight errors in technical drawings, and suggest alternative design configurations based on user input (Li et al. 2024a, b).

In technical drafting and design education, students benefit from AI features that support visualization, spatial interpretation, measurement accuracy, and model refinement. Studies report that AI-assisted design environments strengthen competencies such as creativity, critical reasoning, and design decision making (Fan & Zhong, 2022; Onatayo et al., 2024). Virtual simulation environments further allow students to visualize complex structures, test design iterations, and explore material properties in ways that traditional teaching methods cannot easily replicate. Although these advantages are increasingly recognized, challenges persist in fully integrating AI tools into technical drafting and design curricula, particularly in relation to training, access, and user readiness.

Evolution of digital design technologies and emergence of AI-driven virtual simulation apps

Digital tools used in technical drafting and design have evolved significantly over the past three decades. Earlier software such as AutoCAD, SolidWorks, and SketchUp primarily focused on manual input and rule-based modeling, requiring users to construct drawings or models step by step (Friel, 2015). These tools supported digital workflows but offered limited automation or adaptive feedback.

Recent advancements have introduced AI capabilities that fundamentally change how digital design tools operate (Li et al. 2024a, b; Liang 2024; Onatayo et al. 2024). Modern AI-augmented design platforms now include:

- Predictive drawing and automated corrections that detect geometry errors, inconsistencies, or missing constraints;
- Generative design functions that propose multiple design alternatives based on con-

straints entered by the user;
- Real-time feedback systems that evaluate proportions, alignment, and feasibility of constructed elements;
- Intelligent simulation engines that automatically analyze load, motion, or structural behavior; and.
- Adaptive learning systems that tailor tutorials or challenges based on student performance.

These capabilities are increasingly embedded in apps used in technical drafting and design education, such as Autodesk SketchBook, SketchUp with AI plugins, Onshape Intelligent Tools, and other AI-augmented modeling platforms. From a technology and design education perspective, AI-driven virtual simulation apps represent a shift from tool-centered learning to system-supported learning, where students engage with intelligent environments that scaffold skill acquisition, design iteration, and problem solving (Mangubat, J.C. et al., 2025a; Yu, 2025). This evolution underscores the need to understand how students perceive and adopt such AI-enhanced applications.

Educational technologies in technical drafting and design

The use of digital tools in technical drafting and design education has long been studied, particularly through theoretical models such as the TAM and the UTAUT. These frameworks highlight factors such as perceived usefulness, perceived ease of use, and social influence as key predictors of technology adoption (Davis, 1989; Venkatesh et al., 2003).

Research in design-related disciplines shows that while students recognize the value of digital design tools for improving visualization, accuracy, and productivity, obstacles such as insufficient training, limited access to updated software, and inconsistent institutional support can hinder adoption (Mhlongo et al., 2023; Timotheou et al., 2022). Social influence also plays an important role, particularly in collaborative technical fields. Instructor modeling, peer encouragement, and exposure to industry-standard technologies contribute to more positive adoption attitudes (Wang et al., 2023; Esangbedo et al., 2023; Kamalov et al., 2023). In contexts where students lack such exposure or support, adoption rates tend to be lower.

Factors influencing the use of AI-driven virtual simulation apps

Students' intentions to use AI-driven virtual simulation apps are influenced by both internal and external variables. Perceived usefulness, which refers to beliefs about whether these tools enhance learning performance, has consistently been linked to adoption, especially when AI features directly support accuracy, creativity, and efficiency in technical drafting and design (Haleem et al., 2022; Lai et al., 2012). Perceived ease of use also remains critical, as students new to advanced design technologies may feel discouraged if AI features appear complicated or unintuitive (Zhou et al., 2022).

External conditions also shape adoption. Facilitating conditions such as hardware availability, access to stable software, and presence of technical support influence students' decision to incorporate simulation tools into their coursework (Gkrimpizi et al., 2023). Social influence similarly affects adoption through collaboration, instructor expectations, and peer norms (Shao et al., 2024; Radianti et al., 2019). Despite the growing body of adoption research, few studies focus specifically on AI-driven virtual simulation apps in technical drafting and design contexts. This gap suggests the need for more discipline-focused and AI-specific investigations.

Theoretical basis and hypothesis development

Theoretical basis

This study is anchored in the TAM proposed by Davis (1989), which explains technology adoption through two core determinants: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU refers to the extent to which individuals believe that using a technology will improve their performance, while PEOU captures the degree of effort required to use the technology. TAM has become one of the most influential frameworks for understanding technology acceptance in educational contexts, particularly in studies involving digital learning tools, virtual environments, and interactive applications (Venkatesh & Bala, 2008).

In the context of AI-driven virtual simulation apps used in technical drafting and design education, the traditional TAM variables may not fully capture the unique cognitive, affective, and operational characteristics introduced by AI. Unlike conventional digital tools, AI systems offer adaptive feedback, predictive modeling, and real-time creative augmentation, which influence how students perceive their usefulness and ease of use. To address this, the present study extends TAM by incorporating three AI-specific constructs: Perceived AI Support (P-AIS), Perceived AI Trustworthiness (P-AITR), and Perceived AI Creativity Enhancement (P-AICE). These constructs reflect students' beliefs about AI's instructional responsiveness, reliability, and capacity to enhance creative design processes, elements increasingly emphasized in emerging research on AI-assisted learning.

In addition, the model integrates three external factors, Computer Self-Efficacy (CSE), Facilitating Conditions (FC), and Perceived Risk (PR), to better account for individual confidence, resource availability, and concerns about AI usage. These factors are widely recognized in extended technology adoption models and serve as predictors of PEOU in educational settings (Compeau & Higgins, 1995; Venkatesh & Davis, 2000). The integration of TAM with these additional constructs results in a comprehensive model (see Fig. 1) that examines the factors influencing technology students' intentions to use AI-driven virtual simulation apps in technical drafting and design education.

Hypothesis development

The adoption of AI-driven virtual simulation apps in technical education, particularly in technical drafting and design education, can be better understood by examining a combination of key constructs derived from the TAM and extended frameworks (Davis, 1989; Venkatesh & Bala, 2008). This section presents the development of hypotheses based on the relationships between these constructs.

As the core component of the TAM, PU plays a significant role in determining students' Behavioral Intention (BI) to use technology (Davis, 1989; Venkatesh et al., 2003). PU refers to the degree to which students believe that using AI-driven virtual simulation apps

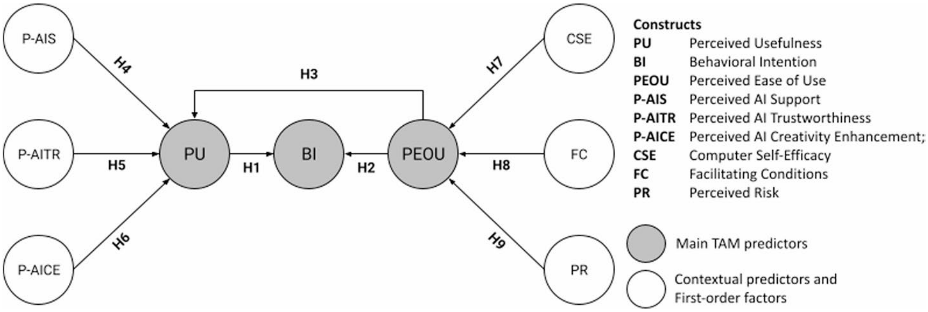

Fig. 1 Proposed model with hypothesized paths

enhances their learning outcomes. Previous research has shown that when students perceive a tool as useful, they are more likely to adopt it (Ayanwale & Ndlovu, 2024; Chan & Hu, 2023; Venkatesh & Davis, 2000). Therefore, it is hypothesized that:

H1: PU will have a positive influence on BI to use AI-driven virtual simulation apps.

PEOU has been shown to positively influence both PU and BI (Davis, 1989; Taylor & Todd, 1995; Venkatesh et al., 2003). The easier students find the technology to use, the more likely they are to perceive it as useful and to intend to use it (Venkatesh & Bala, 2008; Taylor & Todd, 1995). Additionally, students who find the technology easy to use are more likely to develop a positive attitude towards its adoption (Ayanwale & Ndlovu, 2024; Chan & Hu, 2023; Taylor & Todd, 1995; Venkatesh & Davis, 2000). Thus, the following hypotheses are proposed:

H2: PEOU will have a positive influence on BI to use AI-driven virtual simulation apps.
H3: PEOU will have a positive influence on PU of AI-driven virtual simulation apps.

The unique characteristics of AI-driven tools require additional constructs that influence students' perceptions of usefulness. Specifically, P-AIS, P-AITR, and P-AICE all play crucial roles in shaping students' perceptions of the technology's utility. When students perceive the AI system as supportive (Shen & Cui, 2024), trustworthy (Li et al. 2024a, b), and able to enhance their creativity (Ivcevic & Grandinetti, 2024), they are more likely to view it as useful in their learning. Therefore, the following hypotheses are proposed:

H4: P-AIS will have a positive influence on PU of AI-driven virtual simulation apps.
H5: P-AITR will have a positive influence on PU of AI-driven virtual simulation apps.
H6: P-AICE will have a positive influence on PU of AI-driven virtual simulation apps.

Several individual and contextual factors influence how students perceive the ease of use of AI-driven virtual simulation apps. CSE, FC, and PR are constructs that have been found to affect PEOU (Compeau & Higgins, 1995; Venkatesh & Davis, 2000; Featherman & Pavlou, 2003). Students with higher self-efficacy in using technology and better access to facilitating conditions (such as resources and support) are likely to perceive the tools as easier to use (Compeau & Higgins, 1995; Venkatesh & Bala, 2008). On the other hand, students who perceive higher risks in using AI tools may find them more challenging to use (Chan & Hu, 2023; Stöhr et al., 2024). The following hypotheses are proposed:

H7: CSE will have a positive influence on PEOU of AI-driven virtual simulation apps.
H8: FC will have a positive influence on PEOU of AI-driven virtual simulation apps.
H9: PR will have a negative influence on PEOU of AI-driven virtual simulation apps.

Methodology

Research design

This study employed a cross-sectional research design, collecting data from technology students enrolled in technical drafting and design at a single point in time. This design was chosen for its efficiency in examining the relationships between constructs, as well as its ability to provide a snapshot of the factors influencing students' behavioral intentions to use AI-driven virtual simulation apps (Creswell & Creswell, 2020).

The study applied Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the hypothesized relationships among the constructs. PLS-SEM was selected for several reasons. First, it is particularly suitable for predictive and exploratory studies focusing on complex relationships between latent constructs (Hair et al., 2021). Second, PLS-SEM is robust in handling non-normal data distributions and small to moderate sample sizes, both of which are common in educational research (Chin, 1998). Additionally, the method's ability to simultaneously evaluate measurement and structural models provides a comprehensive assessment of both the reliability and validity of constructs and the strength of hypothesized paths. This dual functionality makes PLS-SEM a powerful tool for addressing the research objectives of this study.

To evaluate the measurement model, Confirmatory Factor Analysis (CFA) was performed. Key criteria, including factor loadings, composite reliability (CR), and average variance extracted (AVE), were assessed to ensure construct reliability and validity (Fornell & Larcker, 1981). Factor loadings greater than 0.70 were considered acceptable for item reliability, while CR values above 0.70 confirmed construct reliability. AVE values exceeding 0.50 established convergent validity, demonstrating that the items adequately captured the intended constructs. This rigorous evaluation of the measurement model ensured its robustness before proceeding with the structural model analysis (Hair et al., 2021).

Survey instrument

The survey instrument for this study was designed to assess the factors influencing technology students' intentions to use AI-driven virtual simulation apps in technical drafting and design education. The constructs measured in the survey are outlined in Table 1, which were adapted and modified from previous research to better align with the study's objectives. To ensure the completeness, clarity, and readability of the questionnaire, an expert panel comprising researchers and language specialists reviewed the initial draft (Ranganathan et al., 2024). Based on their feedback, several revisions were made, including the addition of new items to capture aspects of students' intentions to use AI-driven virtual apps. Furthermore,

Table 1 Survey questionnaire constructs and definition of latent variables

Construct	Description	Item Code	Item Statement	Source
Perceived Usefulness	The degree to which a student believes that using AI-driven virtual simulation apps will enhance their learning in technical drafting and design education.	PU1	I believe AI-driven virtual simulation apps will improve my performance in drafting tasks.	Davis (1989); Venkatesh et al. (2003); Venkatesh and Bala (2008)
		PU2	Using AI-driven virtual simulation apps will make the learning process easier in design education.	
		PU3	AI-driven virtual simulation apps will help me create better sketches in my assignments.	
		PU4	I think AI-driven virtual simulation apps can enhance my creativity in design projects.	
		PU5	Using AI tools in my learning will help me complete design tasks more efficiently.	
Behavioral Intention (BI)	The degree to which technology students are motivated to adopt and use AI-driven virtual simulation apps in their academic work.	BI1	I intend to use AI-driven virtual simulation apps in my drafting and design tasks regularly.	Davis (1989); Venkatesh et al. (2003); Taylor and Todd (1995)
		BI2	I plan to explore more AI-driven virtual simulation apps for my academic work in the future.	
		BI3	I am likely to recommend AI-driven virtual simulation apps to my peers for drafting and design activities.	
		BI4	I am willing to invest time and effort to learn how to effectively use AI-driven virtual simulation apps.	
		BI5	I feel motivated to rely on AI-driven virtual simulation apps for improving my design outcomes.	
Perceived Ease of Use (PEOU)	The extent to which a student believes that using AI-driven virtual simulation apps is easy to use and learn.	PEOU1	I find AI-driven virtual simulation apps easy to use.	Davis (1989); Venkatesh et al. (2003); Venkatesh and Bala (2008)
		PEOU2	It is easy to become skillful at using AI-driven virtual simulation apps.	
		PEOU3	I believe AI-driven virtual simulation apps are user-friendly.	
		PEOU4	The interface of AI-driven virtual simulation apps is easy to navigate.	
		PEOU5	I feel confident in using AI-driven virtual simulation apps without much help.	
Perceived AI Support (P-AIS)	The extent to which a student feels that AI provides adequate support for creative tasks and learning.	P-AIS1	AI-driven virtual simulation apps provide helpful suggestions for improving my design work.	Shen and Cui (2024)
		P-AIS2	AI helps me to solve design problems quickly and accurately.	
		P-AIS3	The AI-powered features in simulation apps make my learning process more efficient.	
		P-AIS4	AI in virtual simulation apps offers solutions that enhance my creativity.	
		P-AIS5	I find the AI assistance in simulation apps valuable for improving my design skills.	

Table 1 (continued)

Construct	Description	Item Code	Item Statement	Source
Perceived AI Trustworthiness (P-AITR)	The degree to which students believe that AI tools are reliable, accurate, and trustworthy for design tasks.	P-AITR1	I trust AI-driven virtual simulation apps to provide accurate design suggestions.	Li et al. (2024a, b)
		P-AITR2	I believe AI-powered simulation apps will not make errors in my design work.	
		P-AITR3	I trust the AI in virtual simulation apps to recommend relevant design features.	
		P-AITR4	AI-driven simulation apps can be relied upon to enhance my learning experience.	
		P-AITR5	I am confident that the AI in simulation apps will improve my design output.	
Perceived AI Creativity Enhancement (P-AICE)	The extent to which AI tools are perceived to enhance students' creativity in technical drafting and design tasks.	P-AICE1	AI-driven virtual simulation apps enhance my ability to generate creative design ideas.	Ivcevic and Grandinetti (2024)
		P-AICE2	I believe AI helps me come up with innovative designs that I wouldn't have thought of on my own.	
		P-AICE3	The AI features in simulation apps encourage me to think more creatively in design.	
		P-AICE4	I feel that AI-driven apps help me push the boundaries of my design creativity.	
		P-AICE5	Using AI tools in drafting tasks has made me more creative in my designs.	
Computer Self-Efficacy (CSE)	Students' confidence in their ability to use computers and related technologies effectively.	CSE1	I am confident in my ability to use technology for design tasks.	Compeau and Higgins (1995)
		CSE2	I am comfortable using digital tools to complete design assignments.	
		CSE3	I believe I can use AI-powered tools in design tasks effectively.	
		CSE4	I feel skilled when using technology to create sketches or designs.	
		CSE5	I am confident in my ability to learn new design technologies quickly.	
Facilitating Conditions (FC)	The availability of resources and support that enable the effective use of AI tools in education.	FC1	I have access to the necessary resources to use AI-driven virtual simulation apps.	Venkatesh et al. (2003)
		FC2	There is adequate support for learning how to use AI-driven virtual simulation apps.	
		FC3	I have sufficient hardware and software to effectively use AI tools in my studies.	
		FC4	The institution provides enough training and support to use AI-driven simulation apps.	
		FC5	I can access AI-driven virtual simulation apps anytime I need to use them for design tasks.	
Perceived Risk (PR)	The students' perceptions of the risks involved in using AI tools, such as privacy concerns, errors, or misuse.	PR1	I am concerned about the security of my data when using AI-driven virtual simulation apps.	Featherman and Pavlou (2003)
		PR2	I worry that AI-driven simulation apps might not work as expected during critical design tasks.	
		PR3	I am concerned about the possible misuse of AI in design processes.	
		PR4	I am worried about the privacy of my personal information when using AI tools.	
		PR5	I feel uneasy about depending on AI-driven tools for my design work.	

the language and structure of some statements were simplified to improve comprehension and ensure that the questionnaire was accessible to all participants.

A pilot test was conducted with 30 technology students who were not part of the actual sample. This pilot test yielded Cronbach's alpha values ranging from 0.87 to 0.96, indicating high internal consistency and reliability of the instrument (Taber, 2017). The final version of the questionnaire was organized into two main sections. The first section gathered demographic information, such as age, sex, year level, course and specialization, and prior usage and familiarity with AI-driven virtual simulation apps. The second section consisted of 45 items designed to evaluate key factors related to several constructs, including PU, BI, PEOU, P-AIS, P-AITR, P-AICE, CSE, FC, and PR. Each item was measured using a 5-point Likert scale, with responses ranging from 1 (strongly disagree) to 5 (strongly agree), allowing for a comprehensive understanding of students' perceptions and attitudes toward using AI-driven virtual simulation apps in their coursework.

Participants and data collection

The participants in this study were first-year to fourth-year students enrolled in the College of Technology of a public, non-sectarian, state-funded higher education institution located in Central Visayas, Philippines. These students were selected for their relevance to the study, as they are currently engaged in coursework related to design and drafting, making them ideal candidates for examining their intentions to use AI-driven virtual simulation apps. Their academic experience in technical drafting and design ensures that they possess the necessary background to provide informed perspectives on the use of such technological tools in their coursework.

Recruitment of participants was conducted using purposive-convenience and chain referral sampling methods. Purposive-convenience sampling was chosen as it allows for the selection of participants who are specifically relevant to the study's objectives—those with coursework in design and drafting. This method is practical, considering the targeted population within the College of Technology. The chain referral method was used to further extend participant recruitment through class representatives and program advisers, who assisted in the distribution of the survey link, ensuring broader outreach within the student body (Memon et al., 2017; Kohler, 2019).

The non-probability sampling methods, specifically purposive-convenience and chain referral, were justified as they are appropriate for exploratory research where the goal is not to generalize the findings to the broader population but rather to gain in-depth insights from a specific group of individuals with relevant characteristics. These methods enable the study to focus on students who are directly relevant to the research topic, ensuring the data collected aligns with the research objectives.

Data collection took place between November and mid-December 2024, using an online self-administered questionnaire via Google Forms. This format allowed for efficient and convenient data collection, ensuring accessibility for all participants. Ethical considerations were strictly adhered to throughout the process (Holtz et al., 2024). Informed consent was obtained from all participants, and the study followed the guidelines outlined in the Declaration of Helsinki and Republic Act 10,173, the Data Privacy Act of 2012, ensuring participants' rights and confidentiality were fully respected during the data collection process.

The demographic profile of the participants in this study (Table 2), comprising 493 technology students, reveals a diverse sample across various categories. The participants' ages ranged from 18 to 24 years and older, with the majority falling within the 18–19 age group (38.7%), followed by those aged 22–23 (27.4%), 20–21 (25.7%), and 24 and above (8.1%). The sample consisted predominantly of female students (61.5%), with male students accounting for 38.5%. In terms of year level, first-year students made up the largest proportion (41.8%), followed by second-year students (24.1%), third-year students (20.3%), and fourth-year students (13.8%).

Regarding degree programs and specializations, the participants were enrolled in a variety of Bachelor of Industrial Technology (BIT) programs, with BIT Drafting Technology having the highest number of respondents (27.1%), followed by BIT Interior Design Technology (24.7%), and BIT Civil Technology (5.5%). Other BIT specializations, such as Automotive Technology, Electrical Technology, Electronics Technology, and Furniture and Cabinet Making, were also represented, although with fewer participants. Additionally, students enrolled in Bachelor of Science (BS) programs, such as Graphics Design (15.6%) and Mechatronics (4.1%), were included in the sample.

Table 2 Participants' demographic profile (*n*=493)

Profile	Category	*n*	%
Age (years)	18–19	191	38.7
	20–21	127	25.7
	22–23	135	27.4
	24 and above	40	8.1
Sex	Male	190	38.5
	Female	303	61.5
Year level	First Year	206	41.8
	Second Year	119	24.1
	Third Year	100	20.3
	Fourth Year	68	13.8
Degree and specialization	BIT Automotive Technology	26	5.3
	BIT Civil Technology	27	5.5
	BIT Drafting Technology	134	27.1
	BIT Electrical Technology	32	6.5
	BIT Electronics Technology	26	5.3
	BIT Furniture and Cabinet Making	18	3.7
	BIT Interior Design Technology	122	24.7
	BIT Refrigeration and Air-conditioning Technology	9	1.8
	BIT Welding and Fabrication Technology	2	0.4
	BS Graphics Design	77	15.6
	BS Mechatronics	20	4.1
Prior usage and familiarity with AI-driven virtual simulation apps	Used regularly for academic purposes	49	9.9
	Used occasionally for both academic and personal use	270	54.8
	No prior usage but have heard about AI-driven apps	103	20.9
	No prior usage and unfamiliar with AI-driven apps	70	14.2

When considering prior usage and familiarity with AI-driven virtual simulation apps, the majority of participants reported using these apps occasionally for both academic and personal purposes (54.8%). A smaller proportion of students had used AI-driven apps regularly for academic purposes (9.9%), while 20.9% had heard of these apps but had no prior usage, and 14.2% were unfamiliar with AI-driven virtual simulation apps. This diverse distribution of prior exposure and familiarity with AI tools offers a comprehensive view of students' experiences and attitudes toward adopting AI-driven apps in their academic work.

Data analysis

Data analysis for this study was conducted using Microsoft Excel for summarizing demographic information and SmartPLS 4.0 for descriptive statistics and PLS-SEM. PLS-SEM was chosen due to its ability to model complex relationships between latent constructs and its suitability for exploratory research (Hair et al., 2021).

The adequacy of the sample size was ensured by following the rule of thumb that the minimum number of responses should be at least ten times the maximum number of arrows pointing to any latent variable in the PLS path model. With four arrows pointing to PU, a minimum of 40 responses was required. The actual sample of 493 respondents far exceeded this threshold, ensuring robust statistical power and reliable parameter estimates (Hair & Alamer, 2022). Additionally, the total number of students in the College of Technology during the first semester of the 2024–2025 academic year was 5,965. The sample of 493 students, representing approximately 8.26% of the total population, is deemed sufficient to draw conclusions, aligning with commonly accepted practices for sampling large populations in behavioral research (Creswell & Creswell, 2020).

The data analysis was conducted in three main steps. First, a CFA was performed to evaluate the validity and reliability of the measurement model, including convergent and discriminant validity assessments. Second, standardization and correlation coefficient computation were performed to examine the relationships between constructs. Finally, structural model fit assessments were conducted to evaluate the path coefficients, R^2 values, and predictive relevance (Q^2) of the model (Sarstedt & Cheah, 2019). These steps ensured that the analysis provided accurate and comprehensive insights into the factors influencing technology students' intentions to use AI-driven virtual simulation apps.

To further assess the robustness of the findings, a post-hoc power analysis was conducted for PU, the most complex endogenous construct with four predictors and an R^2 of 0.804. The computed effect size was $f^2 = 4.102$, with a non-centrality parameter (λ) of 2022.286, numerator degrees of freedom = 4, and denominator degrees of freedom = 488. The critical F value at $\alpha = 0.05$ was 2.390, yielding a post-hoc power ($1-\beta$) of 1.0, indicating extremely high statistical power and strong confidence in the reliability of the model estimates (Faul et al., 2009). The corresponding post-hoc power plot is presented in Fig. 2.

Results and findings

This study employed PLS-SEM to examine the relationships among constructs, PU, BI, PEOU, P-AIS, P-AITR, P-AICE, CSE, FC, and PR. PLS-SEM was selected due to its ability to handle complex models with multiple constructs and indicators, making it suitable

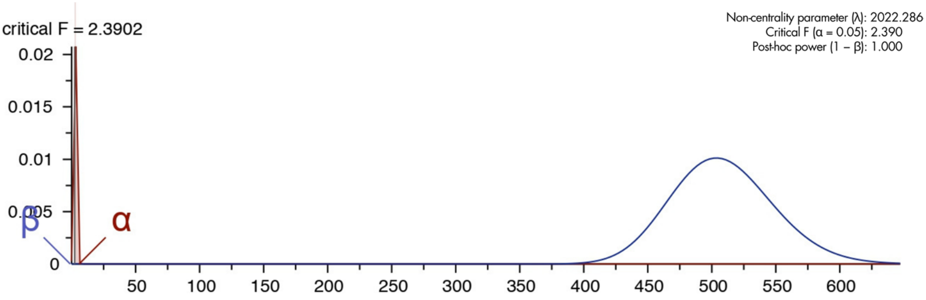

Fig. 2 Post-hoc power plot for latent variable analysis

for the sample size of 493 respondents (Hair & Alamer, 2022). Its robustness in addressing smaller sample sizes, non-normal data distributions, and exploratory research makes it ideal for predictive analysis in this context. PLS-SEM's focus on maximizing shared variance between latent variables provides a comprehensive understanding of the relationships within the model (Dash & Paul, 2021). This section includes descriptive statistics, an assessment of the measurement model to evaluate validity and reliability, and an evaluation of the structural model to test the hypothesized relationships. This methodological approach ensures a theoretically grounded and empirically robust exploration of the factors influencing technology students' intentions to use AI-driven virtual simulation apps in technical drafting and design education.

Descriptive statistics and assessment of the measurement model

The descriptive statistics in Table 3 highlight participants' perceptions and attitudes toward AI-driven virtual simulation apps. The mean scores across constructs ranged from 2.25 to 3.41, indicating moderate levels of agreement with the survey items. Constructs such as PU and CSE had relatively higher mean scores, suggesting positive perceptions of AI-driven tools in supporting academic tasks. In contrast, PR recorded the lowest mean values (2.25–2.48), reflecting participants' apprehension regarding potential risks associated with AI use. Standard deviations, which varied between 0.95 and 1.23, indicate a reasonable level of variability in participant responses.

Factor loadings across all constructs exceeded the recommended threshold of 0.60 (Hair et al., 2022), confirming the reliability of individual items. Cronbach's alpha values ranged from 0.913 to 0.950, while CR values ranged from 0.935 to 0.962, indicating strong internal consistency across constructs. The AVE values for all constructs surpassed the minimum threshold of 0.50, with values between 0.743 and 0.838, demonstrating good convergent validity. These reliability and validity measures affirm the robustness of the measurement model and the constructs' appropriateness for structural analysis.

A closer look at each construct reveals unique insights. PU had mean scores ranging from 3.13 to 3.37 and high factor loadings (0.896–0.922), indicating that participants recognized the utility of AI tools for academic purposes. BI exhibited exceptionally high factor loadings (0.612–0.979), with mean scores suggesting a strong likelihood of adopting AI-driven tools. PEOU had slightly lower mean scores (e.g., 2.93), hinting at potential usability concerns despite its reliable factor loadings (0.819–0.906). P-AIS and P-AITR also demonstrated

Table 3 Descriptive statistics, factor loadings, and reliability measures for the model constructs

Constructs	Item	Mean	SD	Factor loading	Cronbach's alpha	Composite Reliability	Average Variance Extracted (AVE)
Perceived Usefulness (PU)	PU1	3.16	1.07	0.903	0.948	0.960	0.827
	PU2	3.37	1.12	0.896			
	PU3	3.13	1.14	0.914			
	PU4	3.30	1.14	0.913			
	PU5	3.31	1.22	0.922			
Behavioral Intention (BI)	BI1	3.39	1.09	0.612	0.945	0.962	0.838
	BI2	3.35	1.23	0.974			
	BI3	3.32	1.21	0.976			
	BI4	3.34	1.20	0.979			
	BI5	3.32	1.22	0.977			
Perceived Ease of Use (PEOU)	PEOU1	3.33	1.08	0.866	0.913	0.935	0.743
	PEOU2	3.09	1.06	0.819			
	PEOU3	3.25	1.06	0.856			
	PEOU4	3.19	0.98	0.906			
	PEOU5	2.93	1.10	0.862			
Perceived AI Support (P-AIS)	P-AIS1	3.30	1.11	0.900	0.950	0.962	0.834
	P-AIS2	3.17	1.08	0.903			
	P-AIS3	3.21	1.07	0.917			
	P-AIS4	3.21	1.10	0.920			
	P-AIS5	3.19	1.09	0.924			
Perceived AI Trustworthiness (P-AITR)	P-AITR1	3.01	1.10	0.885	0.927	0.944	0.773
	P-AITR2	2.62	1.08	0.810			
	P-AITR3	3.00	1.00	0.901			
	P-AITR4	3.05	1.03	0.888			
	P-AITR5	3.06	1.04	0.907			
Perceived AI Creativity Enhancement (P-AICE)	P-AICE1	3.16	1.08	0.922	0.943	0.956	0.815
	P-AICE2	3.19	1.09	0.860			
	P-AICE3	3.10	1.09	0.908			
	P-AICE4	3.14	1.00	0.916			
	P-AICE5	3.04	1.02	0.905			
Computer Self-Efficacy (CSE)	CSE1	3.24	1.10	0.884	0.927	0.945	0.774
	CSE2	3.27	1.09	0.920			
	CSE3	3.13	1.04	0.881			
	CSE4	3.23	1.11	0.869			
	CSE5	3.41	1.02	0.842			
Facilitating Conditions (FC)	FC1	2.94	0.98	0.904	0.926	0.944	0.773
	FC2	3.08	0.95	0.854			
	FC3	2.81	1.02	0.883			
	FC4	2.88	1.03	0.881			
	FC5	2.90	1.07	0.872			
Perceived Risk (PR)	PR1	2.44	1.13	0.880	0.926	0.944	0.773
	PR2	2.48	1.09	0.878			
	PR3	2.34	1.10	0.919			
	PR4	2.25	1.13	0.914			
	PR5	2.48	1.11	0.799			

strong reliability, though P-AITR recorded lower mean scores (e.g., 2.62), possibly indicating skepticism toward AI reliability. Constructs like P-AICE, CSE, and FC had moderate mean scores and consistently high factor loadings, emphasizing their relevance in the adoption of AI-driven tools. Conversely, PR scored the lowest means (2.25–2.48), reflecting concerns about the risks associated with AI use. Collectively, these findings provide a nuanced understanding of participants' perceptions and validate the constructs used in the study.

Building on the previous analysis, Table 4 presents the discriminant validity and correlation matrix of the constructs, offering a detailed assessment of the relationships and distinctiveness among them. The diagonal values represent the square root of the AVE for each construct, which are all above the recommended threshold of 0.70, indicating robust discriminant validity. The off-diagonal values reflect the correlations between constructs, which are generally high, signifying strong interrelations while still supporting discriminant validity based on the Fornell and Larcker (1981) criterion.

PU demonstrates strong correlations with BI (0.921) and P-AIS (0.892), emphasizing the importance of utility perceptions in influencing participants' intentions to use AI-driven tools and their perception of AI's supportive role. BI also shows significant correlations with PEOU (0.759) and P-AICE (0.766), underscoring the role of usability and creativity in shaping adoption intentions. P-AIS displays the highest correlations with both PU (0.892) and P-AICE (0.865), suggesting that perceptions of AI support are closely linked with perceived utility and creativity enhancement.

Interestingly, PR demonstrates negative correlations with all other constructs, with the strongest inverse relationship observed with PU (−0.525) and BI (−0.520). This indicates that higher perceptions of risk are associated with lower perceptions of AI tools' usefulness and reduced intentions to adopt them. Despite its negative correlations, PR maintains

Table 4 Discriminant validity and correlation matrix of constructs

Constructs	PU	BI	PEOU	*P*-AIS	*P*-AITR	*P*-AICE	CSE	FC	PR
Perceived Usefulness (PU)	0.909								
Behavioral Intention (BI)	0.921	0.915							
Perceived Ease of Use (PEOU)	0.774	0.759	0.862						
Perceived AI Support (P-AIS)	0.892	0.866	0.817	0.913					
Perceived AI Trustworthiness (P-AITR)	0.779	0.732	0.744	0.835	0.879				
Perceived AI Creativity Enhancement (P-AICE)	0.797	0.766	0.762	0.865	0.873	0.903			
Computer Self-Efficacy (CSE)	0.718	0.705	0.777	0.741	0.748	0.814	0.880		
Facilitating Conditions (FC)	0.666	0.645	0.683	0.663	0.659	0.663	0.646	0.879	
Perceived Risk (PR)	−0.525	−0.520	−0.466	−0.511	−0.357	−0.477	−0.457	−0.456	0.879

Note: Diagonal values represent the square root of AVE, and off-diagonal values are correlations between constructs

Table 5 Model fit indices of the study

Fit indices	Saturated model	Estimated model
Standard root mean square residual (SRMR)	0.066	0.076
Unweighted least squares fit function (d_ULS)	4.537	6.055
Goodness fit index (d_G)	3.763	4.276
Chi-square	7520.881	8022.801
Normal fit index (NFI)	0.767	0.751

Table 6 Structural model path coefficients, effect size, and hypothesis testing

Hypothesis	β	t-value	f^2	*p*-value	Decision
H1: PU → BI	0.832	27.519	1.892	0.000	Supported
H2: PEOU → BI	0.114	3.280	0.036	0.001	Supported
H3: PEOU → PU	0.119	2.110	0.023	0.035	Supported
H4: P-AIS → PU	0.704	11.725	0.458	0.000	Supported
H5: P-AITR → PU	0.075	1.077	0.006	0.282	Not supported
H6: P-AICE → PU	0.033	0.493	0.001	0.622	Not supported
H7: CSE → PEOU	0.553	9.806	0.502	0.000	Supported
H8: FC → PEOU	0.288	4.972	0.136	0.000	Supported
H9: PR → PEOU	−0.082	2.247	0.015	0.025	Supported

discriminant validity, as its AVE square root value (0.879) exceeds its correlations with other constructs. FC exhibits moderate correlations with constructs like PU (0.666) and PEOU (0.683), highlighting the relevance of environmental and infrastructural support for effective AI integration. Similarly, CSE correlates strongly with PEOU (0.777) and P-AICE (0.814), reinforcing the importance of individual confidence in leveraging technology.

Table 5 provides additional insights into the model fit indices used to evaluate the overall goodness-of-fit for the structural equation model. The Standard Root Mean Square Residual (SRMR) values for the saturated model (0.066) and the estimated model (0.076) are below the acceptable threshold of 0.08, indicating an adequate fit between the observed and predicted data. Similarly, the unweighted least squares fit function (d_ULS) and the goodness fit index (d_G) demonstrate reasonable alignment, with values of 4.537 and 3.763 for the saturated model and 6.055 and 4.276 for the estimated model, respectively. The chi-square values for the saturated and estimated models, 7520.881 and 8022.801, respectively, reflect the complexity of the model, although this measure is sensitive to sample size. Lastly, the Normal Fit Index (NFI) values of 0.767 for the saturated model and 0.751 for the estimated model approach the acceptable threshold of 0.90, suggesting the model could benefit from further refinement to improve its fit.

Analysis of the structural model

The structural model analysis examined the significance, strength, and direction of the hypothesized relationships among the study variables. Table 6 presents the path coefficients, effect sizes (f^2), and hypothesis testing results. The findings show that PU has the strongest direct influence on BI. The path from PU to BI ($\beta = 0.832$, $t = 27.519$, $p < 0.001$) indicates a highly significant and substantial effect, supported by a large effect size ($f^2 = 1.892$).

Perceived Ease of Use (PEOU) also demonstrated a significant but smaller effect on BI ($\beta = 0.114$, $t = 3.280$, $p = 0.001$, $f^2 = 0.036$), suggesting that ease of use contributes meaningfully, though to a lesser extent, to students' intentions to adopt AI-driven virtual simulation apps.

The model further revealed significant relationships among several antecedents. PEOU significantly predicted PU ($\beta = 0.119$, $t = 2.110$, $p = 0.035$), although the associated effect size ($f^2 = 0.023$) was small, indicating a modest influence. Among the AI-related predictors, P-AIS was a strong and significant predictor of PU ($\beta = 0.704$, $t = 11.725$, $p < 0.001$), reflected by a large effect size ($f^2 = 0.458$). In contrast, P-AITR and P-AICE did not significantly predict PU, with their corresponding path coefficients and p-values indicating no meaningful contributions to students' perceptions of usefulness.

For the predictors of PEOU, the model supported strong effects for CSE and FC. CSE emerged as a major predictor ($\beta = 0.553$, $t = 9.806$, $p < 0.001$, $f^2 = 0.502$), underscoring the centrality of students' confidence in their own digital skills. FC also exerted a significant positive influence on PEOU ($\beta = 0.288$, $t = 4.972$, $p < 0.001$), with a moderate effect size ($f^2 = 0.136$). Finally, PR exhibited a significant negative effect on PEOU ($\beta = -0.082$, $t = 2.247$, $p = 0.025$), although its small effect size ($f^2 = 0.015$) suggests that while risk perceptions influence usability perceptions, their practical impact is limited.

Table 7 summarizes the explanatory and predictive capabilities of the model. PU demonstrated strong explanatory power with an R^2 of 0.804 and high predictive relevance ($Q^2 = 0.801$). BI likewise showed strong explanatory power ($R^2 = 0.853$, $Q^2 = 0.753$), indicating that the model predicts behavioral intentions with considerable accuracy. PEOU yielded a moderate R^2 of 0.665 and a Q^2 of 0.657, suggesting satisfactory predictive relevance despite its comparatively lower explanatory power.

Mediation analysis further clarified the mechanisms underlying these relationships. Table 8 presents the bootstrapped indirect effects and bias-corrected confidence intervals. Several significant indirect pathways were identified. CSE showed significant indirect effects on both PU and BI through PEOU, including a sequential mediation pathway (CSE → PEOU → PU → BI), all indicating partial mediation. FC exhibited a significant indirect effect on BI through PEOU, although its remaining indirect pathways were not significant. Among the AI-related constructs, only P-AIS demonstrated a significant indirect effect on BI via PU, reflecting its unique role in shaping usefulness perceptions. PEOU also showed a significant indirect effect on BI through PU. PR had a small but significant indirect effect on BI via PEOU, although its other indirect pathways were non-significant. Overall, the mediation results reinforce the central role of PEOU and PU as the primary conduits through which self-efficacy, facilitating conditions, AI support, and perceived risk influence students' behavioral intentions to adopt AI-driven virtual simulations.

Furthermore, the structural model (see Fig. 3) evaluates the relationships among latent variables influencing technology students' adoption of AI-driven virtual simulation apps in

Table 7 Coefficient of determination and predictive relevance

Endogenous construct	R^2	Q^2	Interpretation
PU	0.804	0.801	Strong explanatory power; good predictive relevance
BI	0.853	0.753	Strong explanatory power; good predictive relevance
PEOU	0.665	0.657	Moderate explanatory power; good predictive relevance

Table 8 Bootstrapped indirect effects and bias-corrected confidence intervals for the mediation analysis

Indirect Path	β (Indirect Effect)	t-value	*p*-value	95% CI (BC)	Mediation
CSE → PEOU → BI	0.063	3.102	0.002	[0.026, 0.106]	Partial
CSE → PEOU → PU	0.066	2.073	0.038	[0.012, 0.140]	Partial
CSE → PEOU → PU → BI	0.055	2.073	0.038	[0.010, 0.116]	Partial
FC → PEOU → BI	0.033	2.567	0.010	[0.012, 0.063]	Partial
FC → PEOU → PU	0.034	1.875	0.061	[0.006, 0.079]	None
FC → PEOU → PU → BI	0.028	1.884	0.060	[0.005, 0.066]	None
P-AICE → PU → BI	0.027	0.495	0.621	[−0.083, 0.132]	None
P-AIS → PU → BI	0.586	10.234	<0.001	[0.465, 0.692]	Partial
P-AITR → PU → BI	0.062	1.071	0.284	[−0.063, 0.166]	None
PEOU → PU → BI	0.099	2.111	0.035	[0.017, 0.204]	Partial
PR → PEOU → BI	−0.009	1.958	0.050	[−0.022, −0.002]	Partial
PR → PEOU → PU	−0.010	1.381	0.167	[−0.031, −0.001]	None
PR → PEOU → PU → BI	−0.008	1.372	0.170	[−0.026, −0.001]	None

Note. Indirect effects were examined using bootstrapping with bias-corrected confidence intervals. Mediation was considered statistically significant when the 95% confidence interval did not include zero and when $p < 0.05$

technical drafting and design education. The model demonstrates that P-AIS is the strongest predictor of PU with a significant path coefficient of 0.704 (t = 11.725), highlighting the critical role of robust and accessible AI support in enhancing perceptions of usefulness. In contrast, P-AITR and P-AICE have negligible and statistically insignificant effects on PU, with path coefficients of 0.075 (t = 1.077) and 0.033 (t = 0.493), respectively. This indicates that while trust and creativity enhancement are desirable features, they do not directly influence students' perceptions of the system's usefulness in this context.

PU emerges as a central construct, significantly influencing both BI (path coefficient = 0.832, t = 27.519) and PEOU (path coefficient = 0.119, t = 2.110). This underscores the critical role of PU in shaping students' adoption intentions and perceptions of the system's simplicity. PEOU also has a direct effect on BI (path coefficient = 0.114, t = 3.280), indicating that ease of use moderately impacts students' behavioral intentions. Furthermore, PEOU positively predicts FC (path coefficient = 0.288, t = 4.972) and negatively predicts PR (path coefficient = −0.082, t = 2.247), suggesting that user-friendly systems enhance environmental support while mitigating perceived risks.

BI plays a significant role as a mediator, strongly predicting CSE with a path coefficient of 0.553 (t = 9.806). This highlights that a strong intention to adopt AI tools fosters students' confidence in handling computer-based tasks. The variance explained (R^2) values further demonstrate the strength of the model, with 80.4% of the variance in PU explained primar-

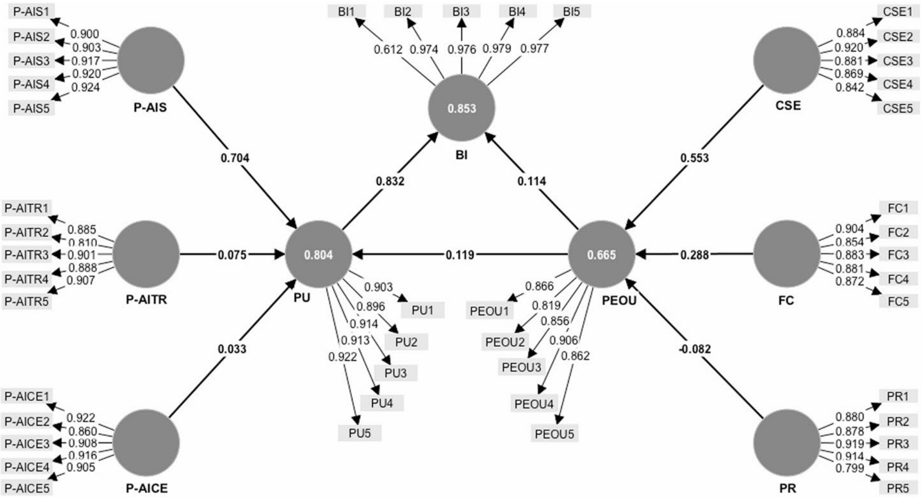

Fig. 3 Path coefficients structural model

ily by P-AIS, 85.3% of the variance in BI explained by PU and PEOU, and 66.5% of the variance in PEOU explained by PU. Lastly, 55.3% of the variance in CSE is attributed to BI.

Overall, the model emphasizes that P-AIS is the most influential exogenous construct, while PU is the most critical mediating factor in predicting BI. The weak effects of P-AITR and P-AICE suggest that students prioritize functional and supportive aspects of AI over trust and creativity when evaluating usefulness. The interplay between PEOU, FC, and PR further highlights the importance of usability and external support in mitigating perceived risks and fostering adoption. These findings suggest that designing AI systems with robust support and clear utility is essential to drive adoption and improve students' confidence in using AI-driven tools.

Discussion

This study examined the factors shaping technology students' intentions to use AI-driven virtual simulation applications in technical drafting and design education. Through PLS-SEM, the study identified the predictive relationships among PU, PEOU, BI, CSE, FC, PR, and AI-related constructs (P-AIS, P-AITR, P-AICE). The use of PLS-SEM is appropriate given its robustness for complex models and its capacity to handle theory-driven structures in educational contexts with moderately sized samples (Hair & Alamer, 2022). Overall, the findings provide valuable insights into student acceptance of AI-enabled design tools, particularly at a time when technology and design education is rapidly evolving in response to sophisticated digital and AI-assisted technologies.

Key findings and theoretical connections

A central finding is the dominant influence of PU on BI ($\beta = 0.832$), reinforcing one of the core premises of TAM (Davis, 1989; Venkatesh et al., 2003). In the design domain, where digital tools shape productivity, visualization, and creative output, students naturally gravitate toward AI-enabled applications that can demonstrably enhance their design performance. Notably, PU was most strongly influenced by P-AIS ($\beta = 0.704$), suggesting that students place significant value on intelligent AI features such as guided support, adaptive feedback, and context-aware suggestions. These results align with recent scholarship showing that AI-supported interventions can enhance students' creativity, especially when accompanied by robust system scaffolds. Bai (2025), for example, demonstrated that well-structured AI assistance strengthens learners' capacity to generate and refine design ideas. Similarly, Özorhon et al. (2025) showed that AI tools in architectural studios provide design cues that help students build conceptual solutions, while Melker et al. (2025) found that AI-based facilitation can enhance both divergent and convergent thinking when positioned as a supportive scaffold rather than an automated producer. Collectively, these studies underscore that AI's usefulness is pedagogical as much as it is computational.

Unexpectedly, the influence of trust in AI (P-AITR → PU) was not significant. This contrasts with earlier studies identifying trust as a key factor in AI acceptance (Afroogh et al., 2024; Kelly et al., 2022). In design contexts where outputs are highly visible and performance-driven, students may prioritize pragmatic considerations, such as accuracy, efficiency, and reliability, over abstract notions of trustworthiness. This pattern aligns with Al-Zahrani's (2024) argument that trust is difficult to establish when AI systems lack transparency. Complementing this, Li et al. (2024b) highlights that trust formation depends on interactions among the user, the system, and the surrounding context; without clear communication, explainability, and user training, trust struggles to take root. These insights collectively suggest that in virtual simulation environments, functional performance may overshadow trust as the basis for perceiving AI tools as useful.

Similarly, P-AICE did not significantly affect PU. Although broader discourse highlights AI's capacity to enhance creativity (Bai, 2025; Ivcevic & Grandinetti, 2024; Melker et al., 2025; Urmeneta & Romero, 2025), its perceived creative potential may be overshadowed in virtual simulation environments where students prioritize features directly linked to precision, rendering quality, and design accuracy. Creativity tends to be valued only when explicitly tied to measurable outputs or assessment criteria. This aligns with Garcia (2024), who notes that the integration of generative AI into artistic and design practices represents a significant cultural shift, one characterized by opportunities for innovation but also by concerns over authenticity, originality, intellectual property, and ethical implications. Such complexities may temper students' immediate perceptions of AI's creative utility, particularly in performance-oriented design tasks.

CSE emerged as a strong predictor of PEOU ($\beta = 0.553$), consistent with classical self-efficacy theory (Compeau & Higgins, 1995) and recent research on AI adoption in design education (Wang et al., 2024). In learning environments where students must navigate intricate digital interfaces and simulation features, higher self-efficacy enables more confident and sustained engagement with AI-driven tools. This aligns with findings by Mangubat et al. (2025a, b), who reported that students with stronger digital self-efficacy demonstrate higher levels of engagement when working with emerging technological tools. Moreover, learners who perceive themselves as competent are more likely to judge AI tools as easy to use, thereby strengthening their adoption intentions, a pattern similarly observed in educational technology acceptance studies (Navarro et al., 2023; Teo, 2011).

FC also positively influenced PEOU (β = 0.288), reaffirming foundational technology acceptance models (Venkatesh et al., 2003) and more recent evidence from design studio contexts (Özorhon et al., 2025). Institutional support, adequate digital infrastructure, and accessible technical scaffolds remain central in enabling students to effectively use advanced simulation technologies. This is supported by Li (2025), who found that facilitating conditions significantly shape students' willingness to use AI-generated content tools, highlighting the importance of strong structural supports, as well as the challenges that arise when such supports are insufficient.

Finally, PR showed consistent negative effects on key acceptance pathways, confirming its role as an emerging barrier to AI adoption. Elevated perceptions of risk, whether related to data privacy, misuse, or overreliance, can diminish students' technological confidence and willingness to experiment (Ali et al., 2023; Balasubramaniam et al., 2023; Rodway & Schepman, 2023). In design education, where iterative exploration is central, PR may restrict students' engagement with AI-enabled features. This aligns with Featherman and Pavlou's (2003) conceptualization of risk as a deterrent to digital adoption and with contemporary findings (Park & Yoon, 2024; Zhao & Khaliq, 2024) noting that fears around AI ethics and transparency can constrain uptake in academic contexts. From a pedagogical standpoint, heightened risk perceptions may hinder the development of technological literacy (the ability to interpret and critically evaluate technological systems) and technological capability (the ability to apply tools in creative and effective ways). As Chen et al. (2025) suggest, generative AI offers expanded opportunities for reflection and metacognition, but learners must feel secure and informed to benefit fully from these features.

Broader implications for technology and design education, practice, and policy

Beyond the statistical findings, this study offers broader insights into how AI-driven virtual simulation applications can reshape learning environments, design pedagogies, and institutional strategies in technology and design education. AI tools present new opportunities to strengthen technological literacy by encouraging students to analyze algorithmic outputs, evaluate AI-generated suggestions, reflect on data flows, and interrogate the ethical implications of machine-assisted decisions. At the same time, they enhance technological capability by supporting realistic design simulations, rapid prototyping, and iterative refinement, allowing students to explore design directions that may be too complex or time-consuming to attempt manually. These outcomes resonate with Melker et al. (2025) and Chen et al. (2025), who emphasize AI's role in deepening metacognition and supporting complex problem–solution navigation.

The findings also highlight the need for curriculum and pedagogical innovation. AI should not be treated as an optional add-on but incorporated across progressive stages of design learning, from foundational principles to advanced creative ideation. Teachers must transition into facilitators of AI-augmented learning, helping students maintain agency while engaging with machine-generated outputs. Assessment practices may also require rethinking, ensuring that evaluation captures process reasoning, originality, and reflective judgment in contexts where AI acts as a creative partner (Gamusa et al., 2026; Garcia et al., 2025).

Addressing PR is crucial for cultivating a safe and supportive learning ecosystem. Clear institutional policies on data governance, transparency of algorithmic operations, and responsible AI use are needed to mitigate concerns and foster trust. Ethical guidelines, instructional modules on responsible AI, and reflective tasks that encourage students to critique AI outputs can further reduce fear and encourage informed experimentation.

The study's findings further inform practice and policy directions. Strengthening PU through demonstration and alignment is essential, as usefulness was the strongest predictor of BI. Integrating AI-driven simulation apps into authentic, performance-based design tasks, showcasing real-world applications, and providing hands-on exposure can help students better appreciate the tools' value. Building students' digital confidence is equally important; structured training programs, capability-building workshops, and faculty development initiatives can reinforce both CSE and FC. Institutions must also prioritize equitable access to AI-ready infrastructure to ensure that opportunities for AI-enhanced learning are distributed fairly across all student groups.

From a policy standpoint, educational institutions should institutionalize responsible AI frameworks, invest in sustainable technological infrastructure, and ensure alignment between academic programs and industry practices where AI-assisted design tools are becoming standard. These strategies ensure that AI integration is purposeful, ethical, and future-oriented rather than superficial or ad hoc (Acut et al., 2026).

The four-quadrant framework (see Fig. 4) visually summarizes the broader implications of AI-driven virtual simulation applications in technology and design education. Each quadrant emphasizes a key dimension:

1. Technological literacy, highlighting students' ability to analyze AI outputs, evaluate suggestions, reflect on data flows, and understand ethical considerations.
2. Pedagogical innovation, showing how teachers act as facilitators, integrate AI across learning stages, and adopt process-oriented assessments;
3. Practice and skills development, emphasizing realistic simulations, rapid prototyping, iterative refinement, and exploration of complex design scenarios; and.
4. Policy and institutional strategies, focusing on responsible AI practices, data governance, and infrastructural support.

Study limitations and future works

Despite the robustness of the findings, this study has several limitations that warrant consideration. First, the study relied on a sample from a single university, limiting the generalizability of the results to other contexts. Future research could replicate this study with a more diverse sample from multiple institutions to enhance the external validity of the findings. Second, the cross-sectional nature of the study restricts the ability to draw causal inferences. Longitudinal studies would be beneficial in understanding how perceptions and behaviors evolve over time as AI tools become more integrated into educational practices.

Additionally, while this study explored the direct and indirect effects of various constructs on students' adoption of AI tools, future research could examine the role of other factors, such as cultural and social influences, that may impact technology adoption in different contexts. Researchers could also investigate how different types of AI tools (e.g., simulation apps, tutoring systems) are perceived and adopted by students in different academic disciplines.

Finally, as AI technology continues to evolve, it will be important for future studies to explore the long-term effects of AI tool adoption on students' learning outcomes and profes-

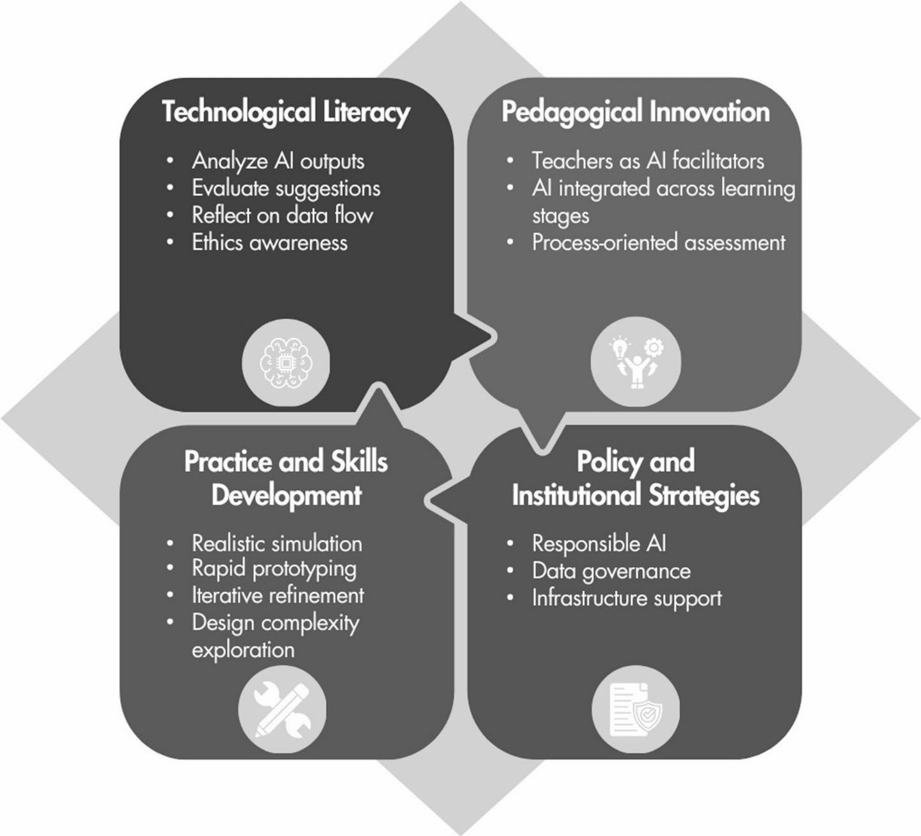

Fig. 4 Key implications of AI-driven virtual simulation for technology and design education

sional competencies. Understanding the broader impact of AI on students' academic success and career readiness will be critical for shaping future educational policies and practices.

Conclusion

This study demonstrates that students' acceptance of AI-driven virtual simulation applications in technical drafting and design education is shaped not only by the perceived usefulness and ease of use of these tools but also, critically, by their perceptions of risk. Concerns related to data privacy, algorithmic opacity, and potential misuse were found to diminish students' confidence in AI technologies, thereby reducing their willingness to integrate these tools into their design learning processes. These findings align with established technology acceptance research yet carry distinct implications for technology and design education—an area where creativity, experimentation, and iterative problem-solving are central to learning.

In design-focused environments, AI-enabled tools increasingly function as co-creators, ideation partners, and generators of alternative design pathways. As such, students must trust these systems not only to handle information responsibly but also to augment, rather than undermine, their creative agency. Addressing perceived risks is therefore essential not just for technology adoption but for safeguarding the development of technological literacy and technological capability, two foundational competencies in technology and design education. Transparent data practices, clear communication of AI system operations, and embedding ethical and responsible AI use within design curricula can help alleviate these concerns. When students feel secure and informed, they are more likely to engage deeply with AI tools, using them to refine ideas, visualize complex concepts, and expand their creative and technical repertoires.

More broadly, the study highlights the transformative potential of AI-driven simulation tools when supported by robust institutional policies, adequate technological infrastructure, and educator preparedness. Educational institutions that cultivate environments balancing innovation with responsibility can empower students to harness AI as an integral component of contemporary design practice.

Future research could extend these insights by examining how students' perceptions evolve over time as AI becomes more deeply embedded in design pedagogies, or by exploring variations across different design disciplines and cultural contexts. Understanding these dynamics will be vital for developing evidence-based frameworks that guide the ethical, effective, and pedagogically meaningful integration of AI in Technology and Design Education.

Abbreviations

AI	Artificial Intelligence
AVE	Average Variance Extracted
BI	Behavioral Intention
CFA	Confirmatory Factor Analysis
CR	Composite Reliability
CSE	Computer Self-Efficacy
FC	Facilitating Conditions
P-AICE	Perceived AI Creativity Enhancement
P-AIS	Perceived AI Support
P-AITR	Perceived AI Trustworthiness
PEOU	Perceived Ease of Use
PLS-SEM	Partial Least Squares Structural Equation Modeling
PR	Perceived Risk
PU	Perceived Usefulness
SEM	Structural Equation Modeling
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology

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Declarations

Ethical considerations All participants provided informed consent prior to their involvement in the study. The research adhered to established ethical guidelines throughout its implementation.

Use of AI in scientific writing The authors confirm that generative AI tools were not utilized in the preparation and finalization of this manuscript.

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