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Humanities and Social Sciences Communications

Article in Press

https://doi.org/10.1057/s41599-026-06713-2

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Received: 17 February 2025

Accepted: 5 February 2026

Cite this article as: Zeng, L., Wang, A., Huang, Y. *et al.* Unveiling college students' adoption of AIGC in design learning: an integrated model. *Humanit Soc Sci Commun* (2026). https://doi.org/10.1057/s41599-026-06713-2

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Unveiling College Students' Adoption of AIGC in Design Learning: An Integrated Model

Abstract

This study investigates the factors that influence college students' intention to use Artificial Intelligence Generated Content (AIGC) technology in design learning. An extended technology use and diffusion model is proposed and validated by integrating the Artificial Intelligence Device Use Acceptance (AIDUA) model with the Innovation Diffusion Theory (IDT). The present study collected data from 385 Chinese college students majoring in design through online surveys. The proposed model, which includes technology concerns, emotional acceptance, and behavioral transformation, was empirically tested using structural equation modeling (SEM) on data collected from students across different academic levels. The research findings suggest that, in the first stage, relative advantage and compatibility exert a significant and positive influence on both performance expectancy and effort expectancy. However, complexity negatively affects both. In the second stage (emotional acceptance), effort expectancy has a highly positive and significant influence on the adoption and diffusion. Conversely, the impact of performance expectancy on use and diffusion is not substantial. In the final stage (behavioral transformation), both social influence and individual innovation positively and significantly impact the use and diffusion of AIGC. Thus, the empirical results support the integration of AIDUA and IDT. This study provides a conceptual AIGC use and diffusion framework that other researchers can use to investigate AIGC-related topics in design learning.

Keywords

AIGC, AIDUA, IDT, Design learning, College Students

1.Introduction

Artificial intelligence (AI) continues to evolve, significantly impacting the relationship between human intelligence and AI. In some cases, artificial intelligence generated content (AIGC) will even outperform the content authored by humans. This paper explores the factors that influence college students' acceptance of AIGC in design learning, especially in the context of human-computer interaction and AI-driven content creation. Empirical analysis shows that when users perceive strong cognitive abilities and relational competencies during interaction, they tend to respond positively to AIGC (Liu et al., 2023).

Design education presents a distinct context for studying AIGC adoption, as it emphasizes creativity, iteration, and visual communication, skills that align closely with the capabilities of AIGC. Recent studies in design education (Tahiru, 2021; Chacko, 2024) show that AIGC enhances student design learning. As AI progresses rapidly, AIGC is increasingly integrated into design education, offering students creative and practical support. Soliman et al. (2024, 2025) and Samala et al. (2025)

explored university students' intention to use AIGC in education by integrating TAM, SDT, and IDT. They used methods such as PLS-SEM, ANN, and fsQCA to examine factors such as perceived usefulness and developing relevant taxonomies. In terms of practical benefits, AIGC can help designers understand users' needs more accurately, quickly generate diversified design plans, and provide strong support during the design iteration. In recent years, numerous studies have shown that AIGC has excellent potential for application in design education. Luo and Wang (2023) discussed the crisis and response for the design discipline in the AIGC era. Their discussion proposed a new approach for using AIGC in design education. However, ethical concerns, such as authorship issues, originality, bias, and over-reliance, pose challenges to AIGC use in design education, raising questions about academic integrity and responsible AI use (Cao et al., 2023; Wong & Looi, 2024). Li (2024) pointed out that when designers use AIGC for design, factors such as perceived anxiety and perceived risk may negatively impact their willingness to use it. These issues suggest the need for a more cautious and structured approach to integrating AIGC into education. In a comprehensive review of AIGC applications in education, Chen et al. (2024) report on how AIGC can be important and valuable in design. Although there is a wealth of research on AIGC, there are at least the following shortcomings: Current research tends to focus more on issues such as originality, ethics, and over-dependence on technology. Their synthesis further reveals that designers' AIGC adoption patterns demonstrate significant susceptibility to perceived anxiety factors. However, it did not profoundly explore students' similar psychological and behavioral responses in design learning. Moreover, researchers emphasized the importance of constructing a comprehensive research agenda to study the practical application of AIGC in education. However, there is no comprehensive and systematic framework and strategy for its application in design learning.

Although AIGC is increasingly used in design education, our understanding of how students respond cognitively, emotionally, and behaviorally remains limited. Most existing research focuses on general adoption or technical aspects but lacks insight into how design learners perceive AIGC's usefulness, complexity, or compatibility during creative learning. With AIGC being rapidly integrated into curricula, these gaps raise urgent questions for educators and researchers about how to support effective and responsible use in real-world learning environments.

To address these research gaps, this study draws upon innovation diffusion theory (Rogers, 1981) and device use acceptance models (Moore & Benbasat, 1991), incorporating constructs such as relative advantage, compatibility, complexity, performance expectancy, and effort expectancy. We adopt the AIDUA model to explore students’ attitudes and behaviors across three sequential phases: technology concern, emotional acceptance, and behavioral transformation. This integrative framework allows us to investigate both the cognitive drivers and social influences behind AIGC adoption in design learning, offering a more comprehensive understanding of how AIGC technologies are perceived, accepted, and internalized by students in creative disciplines. Thus, this study aims to understand the impact of the continuous diffusion and use of AIGC technology among college students in design learning through the evaluation of three stages of AIDUA, combined with the following three questions:

RQ1 The first stage, technology concern: How do innovation characteristics such as relative advantage, complexity, and compatibility affect students' performance expectancy and effort expectancy?

RQ2 The second stage, emotional acceptance: Do performance expectancy and effort expectancy directly affect the use and diffusion behavior of AIGC technology?

RQ3 The third stage, behavioral transformation: Do social influence and individual innovation affect the final adoption and diffusion?

The following chapters will review the literature on AIGC learning behavioral intent. Subsequently, the research methods and data analysis will be detailed, followed by the reporting and discussion of the research findings. Ultimately, we intend to summarize findings and propose avenues for future research. The purpose of this study is to gain a deeper understanding of college students' attitudes and behaviors towards AIGC. According to Wang and Chen (2024), this study provides both theoretical and practical advice for AIGC to be used more widely. Additionally, the research analyzes college students' use and diffusion of new technologies in terms of performance expectancy, effort expectancy, societal influence, and individual innovation. This approach offers suggestions for researchers on improving and optimizing AIGC in design learning.

This research holds both theoretical and practical significance. Theoretically, it enriches the literature on AIGC adoption by introducing a design-education-specific perspective and integrating psychological and social variables into an empirical model. Practically, the findings can inform educators, curriculum designers, and policymakers on how to facilitate responsible and effective AIGC integration in design education. In addition, it offers strategic insights for developing training programs that support ethical awareness and creative agency in the age of AI-enhanced learning.

2.Literature review

2.1 AIGC technology

In the era of rapid technological development, multiple fields have turned their research focus to AIGC, and numerous scholars have researched it from different perspectives. Acheampong et al. (2021) reviewed text-based emotion detection models based on Transformer, offering theoretical support for the employment of AIGC in the natural language processing area. Ackerman (2016) found that people are concerned about identity threats. They are often reluctant to accept anthropomorphic social robots, and psychological barriers to the acceptance of social robots in AI applications have been identified. Alasadi and Baiz (2023) explored AIGC's opportunities, problems, and solutions in education and research, emphasizing its potential and challenges in the educational field. Empirical evidence suggests that users' awareness of AIGC's strong cognitive and relational capabilities in interactions is positively influenced.

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Regarding research on AIGC and design, Jiao et al. (2021) and Jin et al. (2016) investigated the data requirements at different design stages, clarifying the crucial role of data in design innovation. Jin et al. (2025) conducted a systematic inventory of AIGC applications through design innovation processes from product definition to the user experience evaluation phases. They identified systemic implementation challenges associated with AIGC, including limitations in data quality and computational resource constraints. Concurrently, Huang et al. (2024) showed that AIGC can improve students' self-efficacy and the quantity, novelty, and diversity of creative ideas in product design ideation. However, these benefits coexist with reduced conceptual quality outcomes and performance disparities across learners with varying baseline competencies. They further found that AIGC has advantages in enhancing students' self-efficacy, and students with different abilities have different acceptance levels of its learning experience. Therefore, teachers should teach students about their aptitudes. Li (2024) analyzed the factors that impact designers' intention to use AIGC. The findings indicated that performance expectancy, effort expectancy, social influence, and facilitating conditions have a positive effect on designers' intention to use AIGC. In contrast, perceived anxiety and perceived risk have a negative impact. AIGC provides college students with abundant learning resources and creative inspiration in design learning, which can improve learning efficiency and design innovation. However, applying AIGC also brings problems such as originality, ethics, and technical adaptability. These issues require design educators to focus more on the rational application of technology and student creativity.

Research on AIGC applications in some fields has achieved notable results. However, AIGC still faces challenges in data quality, model interpretability, and user acceptance. Future studies should address these challenges to promote the further development and widespread application of AIGC technology.

2.2 IDT and AIDUA

Innovation Diffusion Theory (IDT) explains how innovations are adopted and spread through social systems, emphasizing factors such as relative advantage, compatibility, complexity, trialability, and observability (Dillon & Morris, 1996； Rogers, 2003). Recent studies have confirmed the theory's applicability across educational and commercial contexts. For instance, Pinho et al. (2021) found that compatibility and relative advantage significantly influenced students' engagement with e-learning platforms, while Al-Rahmi et al. (2019) integrated IDT with TAM to examine attitudes toward MOOCs. In non-educational domains, Agag and El-Masry (2016) and Waheed et al. (2015) applied IDT to understand user adoption of online communities and mobile technologies. Despite its strengths, IDT has been critiqued for overlooking the emotional and psychological dimensions of technology adoption (Waheed et al., 2015), prompting scholars to integrate it with models such as TAM, UTAUT, and TRA for improved explanatory power (Claudy et al., 2015; Al-Rahmi et al., 2021). With the rise of AI and AIGC, IDT remains a valuable framework for analyzing how innovation characteristics influence adoption behavior in dynamic digital environments.

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The Artificial Intelligence Device Use Acceptance (AIDUA) model, proposed by Gursoy et al. (2019), builds on cognitive appraisal theory to explain users' acceptance of AI technologies through a three-stage process: primary appraisal, secondary appraisal, and outcome. It incorporates both cognitive (e.g., performance expectancy, effort expectancy) and emotional (e.g., trust, affect) factors, highlighting the roles of social influence, hedonic motivation, and anthropomorphism in shaping user attitudes. Recent studies have applied AIDUA in various domains, including hospitality (Roy et al., 2020) and education (Li, 2024; Huang et al., 2024), demonstrating its utility in understanding technology adoption behaviors in emotionally driven or complex decision-making environments. In AIGC-supported learning, AIDUA helps explain how emotional responses and cognitive evaluations jointly influence students' willingness to adopt. The model's growing relevance reflects a broader shift toward integrating affective dimensions into technology acceptance research (Cintamür, 2024; Ma & Huo, 2023).

The integration of IDT and the AIDUA model provides a comprehensive theoretical lens for understanding the adoption and diffusion of AIGC technologies in design learning contexts. IDT focuses on how innovation characteristics influence adoption behavior, while AIDUA incorporates emotional and cognitive processes to explain user acceptance. According to Rogers (2003), IDT posits that factors such as relative advantage, compatibility, low complexity, trialability, and observability determine the rate and scope of technology diffusion. This theory has been widely applied in educational contexts, such as the adoption of e-learning platforms (Pinho et al., 2021) and MOOC systems (Al-Rahmi et al., 2019). However, a notable limitation of IDT is its lack of attention to emotional and psychological variables, which are essential in understanding users' nuanced behavioral responses (Waheed et al., 2015). To address this gap, the AIDUA model, proposed by Gursoy et al. (2019) and based on cognitive appraisal theory, complements IDT by capturing the emotional stages of user interaction with AI devices. It identifies three sequential phases: primary appraisal, secondary appraisal, and outcome evaluation. In this framework, factors such as social influence, hedonic motivation, anthropomorphism, performance expectancy, and effort expectancy shape users' emotional responses and subsequent behaviors. Positive emotional responses enhance willingness to adopt, while negative emotions deter usage.

Recent studies have demonstrated the relevance of the AIDUA model in AIGC-supported educational contexts. For instance, Li (2024) and Huang et al. (2024) applied AIDUA to examine students' willingness to adopt AIGC tools, highlighting the impact of emotional engagement in learning environments. Likewise, Roy et al. (2020) and Hasija and Esper (2022) validated the model's applicability in service and hospitality domains, showing its generalizability across settings. By combining IDT's emphasis on innovation attributes with AIDUA's focus on emotional-cognitive appraisal, the integrated framework offers a more holistic explanation of AIGC adoption. This synergy is particularly valuable in design learning, where both rational evaluation and emotional resonance influence students' engagement with new technologies. Therefore, this theoretical integration enables a more robust analysis of how and why students adopt and use AIGC tools, as well as how these tools are diffused.

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This study compares the integrated AIDUA and IDT framework with other widely used technology adoption models, such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), the Theory of Reasoned Action (TRA), and the Theory of Planned Behavior (TPB). While these models primarily emphasize cognitive constructs like perceived usefulness, they often overlook affective responses such as anxiety, trust, or emotional acceptance, which are critical in educational contexts. The AIDUA model explicitly incorporates these emotional dimensions, thus enriching explanatory power. In addition, IDT complements AIDUA by offering structural insights into how innovation characteristics, such as relative advantage, complexity, and compatibility, influence adoption at the systemic level. Compared with established models like TAM and UTAUT, which emphasize cognitive and utilitarian aspects of technology adoption but often neglect emotional factors such as anxiety and emotional acceptance, integrating AIDUA and IDT provides a holistic theoretical lens. Specifically, AIDUA complements IDT's lack of emotional factors by explicitly addressing emotional acceptance, while IDT expands AIDUA's explanatory power through its detailed treatment of technology diffusion and innovation characteristics.

2.3 Research gaps

Despite substantial research on AIGC and its educational potential, several research gaps remain unaddressed. Firstly, prior studies predominantly focused on technical adoption, ignoring the nuanced psychological and emotional processes of students, particularly in creative learning contexts such as design education. Secondly, previous research produced conflicting findings regarding the impacts of AIGC. While Huang et al. (2024) found positive effects on self-efficacy and creative ideation quantity, they simultaneously identified negative impacts on conceptual quality and uneven levels of acceptance among students with different baseline abilities. Moreover, Li (2024) highlighted perceived anxiety and risk as significant barriers, contrasting sharply with studies that emphasize positive factors such as performance expectancy and ease of use (Li, 2024). These contradictory results underscore a critical knowledge gap about students' multifaceted psychological experiences. These unresolved issues highlight the necessity of further empirical investigation into students' cognitive, emotional, and behavioral interactions with AIGC technologies. Hence, addressing these gaps directly informs this study's objectives of examining the nuanced mechanisms influencing AIGC adoption in design education comprehensively.

3.Hypothesis development

3.1. The First Stage of AIGC Technology in Design Learning: The Stage of Technology Concern

The innovation diffusion theory (Rogers, 2003) stipulates that relative advantage, complexity, and compatibility are the key determinants of technology adoption. In the context of AIGC applications in

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design learning, these factors also align with the technology concern stage proposed in AIDUA (Gursoy et al., 2019). In this model, users assess AI devices based on their perceived benefits (relative advantage), ease of use (low complexity), and fit with existing workflows (compatibility).

Relative advantages refer to the degree of superiority of an innovation perceived by individuals compared to old ideas, technologies, or methods. Recent studies emphasize that perceived usefulness and added value of AI-driven tools significantly influence adoption in educational contexts (Almassaad et al., 2024; Tariq, 2025). In the early appraisal phase, college students often evaluate whether AIGC technologies reduce cognitive load, increase creative efficiency, or provide novel learning experiences aligned with their design goals. These perceived benefits strongly influence both performance expectancy and effort expectancy (Dahri et al., 2024). When AIGC aligns with users' academic goals and learning values, it reduces perceived uncertainty and fosters a favorable attitude toward adoption (Liu et al., 2025). Building on the related earlier theoretical and empirical discussions, we propose the following hypothesis:

H1. Relative advantages positively affect college students' performance expectancy of AIGC technology in design learning.
H2. Relative advantages positively influence college students' effort expectancy regarding AIGC technology in design learning.

Rogers (2003) described complexity as "the degree to which an innovation is perceived as relatively difficult to understand and use" (p.15). Rogers (2010) posited that, unlike other attributes, complexity has a negative correlation with the adoption rate. Consequently, practical strategies for reducing complexity are needed to help the widespread adoption of innovative technologies. Al-Rahmi et al. (2021) defined complexity as the perceived effort of end users to understand and use a technology. Moreover, according to Parisot (1995), the complexity of different technologies plays a role in the perceived value of AIGC and thus in the adoption rate of new technologies. This is precisely the reason why reducing complexity must be a central focus in enabling the widespread adoption of new technologies. Therefore, the following hypothesis is posited:

H3. Complexity negatively affects college students' performance expectancy regarding AIGC technology in design learning.
H4. Complexity negatively impacts college students' effort expectancy regarding AIGC technology in design learning.

Compatibility refers to the degree to which an innovation aligns with users' existing values, experiences, and practices (Rogers, 2003). When users perceive a technology as highly compatible with their current learning routines and technical infrastructure, they are more likely to expect it to perform well and bring tangible benefits. In the context of design education, if AIGC tools are compatible with students' current digital workflows and creative habits, they are likely to perceive greater performance expectancy due to reduced disruption and enhanced continuity in learning (Hashim et al., 2015; Venkatesh et al., 2012).

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Moreover, compatibility reduces the cognitive and behavioral effort required to adapt to a new system, thereby enhancing effort expectancy. When users perceive a smooth integration between new and existing tools, their perceived difficulty in adopting the innovation decreases, making the technology easier to use (Cimperman et al., 2016). Recent studies in educational technology adoption confirm that compatibility not only enhances the perceived usefulness of AI-powered platforms but also significantly reduces learners' adaptation burden, contributing to their intention to continue using such systems (Waheed et al., 2016; Sun et al., 2024). Therefore, the following hypotheses are proposed:

H5. Compatibility positively affects college students' performance expectancy regarding AIGC technology in design learning.
H6. Compatibility positively influences college students' effort expectancy regarding AIGC technology in design learning.

3.2. The Second Stage of AIGC Technology in Design Learning: The Stage of Emotional Acceptance

Performance expectancy refers to the degree to which a person thinks that making use of a specific technology can assist in enhancing their work or study performance. Performance expectancy is one of the core variables influencing users' acceptance and use of technology (Rizkalla & Bernando, 2024). Effort expectancy refers to the extent to which an individual believes it will be to use a specific technology, that is, the amount of effort an individual perceives they need to put in to use the technology. Effort expectancy represents the users' general impression of how hard it is to use a particular technology. Rizkalla and Bernando (2024) pointed out that it is a key factor affecting whether users will accept and use the technology. Davis (1989) used TAM, which showed that effort expectancy (perceived ease of use) is a major determining factor in user acceptance of technology. Venkatesh et al. (2003) first systematically defined performance and effort expectancy concepts. They identified these as crucial factors affecting users' acceptance and utilization of information technology. Moreover, they validated the substantial influences that performance expectancy and effort expectancy have on users' behaviors. Chavoshi and Hamidi (2019) delved into the functions of performance expectancy and effort expectancy in adopting mobile learning. These two variables significantly influenced students' desire to use AI-driven learning tools.

In the AIGC learning environment, these two variables are significant for understanding students' learning behaviors and attitudes. According to Geiger et al. (1998), students' learning motivation can be evaluated using expectancy theory, and research indicates that effort expectancy has a significant impact on students' motivation and learning behaviors. The discussion by Hew and Brush (2007) on performance and effort expectancy helps in understanding the possible problems and challenges in promoting AI learning at the primary education stage.

The second stage of the AIDUA model primarily examines college students' expectations of how AIGC technology will enhance design learning and work efficiency. It also assesses the perceived effort required during the learning process. This stage investigates whether these factors, the

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continuous use and widespread diffusion of intelligent technologies, are present. The greater the perceived performance of AIGC technology in design learning and the lower the perceived effort, the higher the enthusiasm for continuous learning will be. Additionally, students will be more inclined to disseminate and promote the new technology among friends or classmates. Hence, the following hypothesis is proposed:

H7. Performance expectancy of AIGC technology in design learning positively affects its use and diffusion.
H8. Effort expectancy of AIGC technology in design learning positively influences its use and diffusion.

3.3. The Third Stage of AIGC Technology in Design Learning: The Stage of Behavioral Transformation

Social influence is the degree to which an individual's decision-making process is influenced by external social elements such as the opinions, behaviors, and social norms of others. One of the key factors of adoption and usage of information technology is social influence, according to Venkatesh (2003). In the context of technology acceptance, Ajzen (1991) stressed how social factors shape an individual's technology adoption decision. The opinions and behavior of others whom they observe are considered by Moore and Benbasat (1991) to emphasize the importance of the opinions and behavior of others observed by individuals when deciding whether to adopt new technologies. Taylor and Todd (1995) argued that others' opinions and behaviors significantly impact an individual's willingness and behavior to use information technology. Especially in a work environment, the attitude of colleagues and superiors towards new technology significantly influences an individual's acceptance of it.

Individual innovation refers to the traits and behavioral tendencies of the individual who is willing to try, explore, and adopt new ideas, new technologies, or new methods. It encompasses personal characteristics (e.g., openness to experience, learning agility) and contextual factors (e.g., autonomy, feedback climate) (Anderson & Zhou, 2014; Saad et al., 2021). Agarwal and Prasad (1998) examined how individual-difference factors influence the acceptance of new technologies, with individual innovation being a key variable among them. More recently, studies in AI and education suggest that students with high innovative tendencies are more likely to adopt AIGC tools proactively, often serving as early adopters and influencers within their peer networks (Jiang et al., 2025; Wang et al., 2025). Rogers (2003) considered individual innovation a crucial concept in the innovation-adoption process. Different individuals vary in their speed and willingness to adopt innovations. Early adopters of technologies are individuals who exhibit high levels of innovation and act as prosumers, spreading information and technologies.

In the behavioral transformation stage, a shift towards using AIGC technology is formed based on earlier assessments. In this stage, social influence and individual innovation are effective

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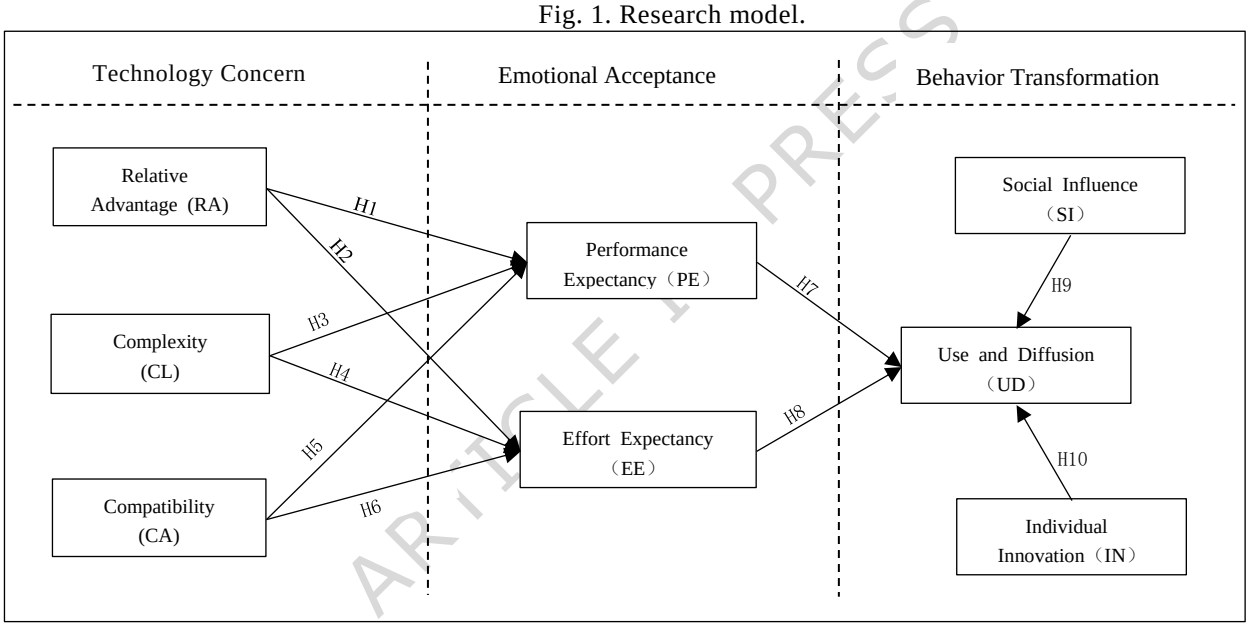
influencing variables of IDT. Simply, the probability of an individual using a new technology is higher if the individual's social circle already uses the technology. Meanwhile, within the realm of technology application, individual innovation is manifested as the likelihood and enthusiasm of individuals to adopt and promote new technologies first. Therefore, both the variables of social influence and individual innovation will positively impact behavioral diffusion. The hypotheses are as follows:

H9. Social influence positively affects the use and diffusion of AIGC in design learning.
H10. Individual innovation positively affects the use and diffusion of AIGC in design learning.

The proposed relationships are shown in Fig. 1.

Fig. 1. Research model.



4.Method

4.1. Participants

The participants in this study were Chinese college students majoring in design, recruited through convenience sampling methods to ensure diversity across graphic design, product design, multimedia design, and film and television animation disciplines. A total of 496 students voluntarily completed an anonymous online questionnaire. To enhance data quality, exclusion criteria were established: questionnaires completed in less than 160 seconds or containing uniform responses were excluded due to likely inattentive responding (e.g., insufficient time to answer 47 items thoughtfully). Ultimately, 385 valid samples were retained. This sample size meets the recommendations for SEM, which suggest 5–10 participants per questionnaire item (Abd-El-Fattah, 2010). Table 1 summarizes participant demographics. The distribution of variables generally satisfied the requirements for

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sampling adequacy. For instance, the gender distribution showed that males accounted for 29.6% and females for 70.4%, indicating a higher representation of female college students. Additionally, the age distribution was primarily concentrated among college students aged 18 to 25, who comprised 84.6% of the sample. Most participants were in the associate degree stage (51.4%) or the undergraduate stage (27.8%).

Table 1 Demographic information of the participants

	Number	Percentage	Number
Gender	Male	114	29.6
	Female	271	70.4
Grade	18~25	326	84.6
	26~30	16	4.2
	31~40	33	8.6
	41~50	6	1.6
	>60	4	1.0
Learning stage	Junior College	198	51.4
	Undergraduate	107	27.8
	Master	45	11.7
	PhD	31	8.1
	Other	4	1.0

4.2. Instruments development

We divided the questionnaire into two parts. The first part was designed to collect demographic data from participants, focusing on gender, grade level, and stage of study. The second section comprised eight subscales, totaling 47 items. These items were adapted from widely recognized and accepted instruments to assess the eight latent variables pertinent to the study. Each subscale employed a 5-point Likert scale format.

The technology concern stage encompasses relative advantage, complexity, and compatibility. It primarily examines how design-major college students' attention to AIGC technology affects their performance expectancy and effort expectancy in design learning. We initially designed each variable with seven questions. For constructs related to relative advantage, complexity, and compatibility, we adapted the survey items primarily from Huang et al. (2020), who examined these constructs in the context of learning and dissemination on open-source learning platforms. We also incorporated items from Prasad Kotni et al. (2023), who explored comparative advantage and compatibility within the IDT framework. Additionally, Pinho et al. (2021) applied IDT to reframe compatibility issues related to electronic technologies in their study.

The stage of emotional acceptance primarily examines the degree to which the three independent variables from the initial stage significantly impact performance expectancy and effort expectancy

among college students using AIGC technology for design learning. In design learning, performance and effort expectancy constitute two fundamental constructs that significantly impact college students' acceptance and use of AIGC for educational purposes. Performance expectancy pertains explicitly to the projected augmentation in learning outcomes and efficiency that students anticipate from utilizing AIGC technology. Conversely, effort expectancy is associated with the perceived simplicity or complexity of employing AIGC. These constructs are indispensable and critical in shaping students' attitudes and behaviors regarding integrating AIGC into their design learning processes. Also, they are vital determinants in understanding the technology adoption and use dynamics in education. We adapted the survey questions regarding performance expectancy from the study by Zhou and Zhang (2024) on AIGC users. Additionally, we rephrased the questions about effort expectancy based on the technology acceptance model for online work by Widianto (2005).

In the behavioral transformation stage, three variables are considered: use and diffusion, social influence, and individual innovation. The survey items designed for this stage aim to comprehensively and effectively assess whether social and individual innovation factors significantly influence college students' continued use and diffusion of AIGC technology. Seven questions were set for the two variables: social influence factors and individual innovation. The content of the questions was adapted from the survey items used by Pinho et al. (2021) and Prasad Kotni et al. (2023) to measure the role of these variables within the framework of the IDT. This adaptation ensures that the survey questions are relevant and reliable. It facilitates a more precise evaluation of the hypothesized relationships among the investigated variables. The details of the instruments were shown in Appendix A.

A pre-testing procedure was conducted with 10 university students to assess item clarity and content validity. Feedback from this pre-test informed revisions, enhancing readability and removing ambiguities. Subsequently, a pilot study involving 50 students was performed to validate instrument reliability. Cronbach's alpha values indicated acceptable reliability ($\alpha > 0.70$) across all constructs. Adjustments based on this pilot improved internal consistency from initial alpha values ranging from 0.65-0.78 to final values of 0.74-0.89.

4.3. Data Analysis

Data analysis was conducted using SPSS 27.0 and AMOS 26.0. Confirmatory Factor Analysis (CFA) was initially performed to validate the measurement model's validity and to handle missing data using maximum likelihood estimation. Structural Equation Modeling (SEM) was subsequently employed due to its effectiveness in simultaneously examining complex relationships between latent constructs. Following the (Abd-El-Fattah, 2010) recommendations, the sample size for conducting CFA was determined based on the criterion of 5 to 10 respondents per survey item. Data screening procedures included checks for outliers, normal distribution, and multicollinearity. Potential biases inherent in self-reported measures were addressed by guaranteeing participant anonymity, emphasizing the confidentiality of responses, and employing validated instruments containing balanced item wording to reduce response bias.

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5. Results

5.1. Results of confirmatory factor analysis

In addition to evaluating the measurement model's reliability and validity based on standardized factor loadings, Cronbach's alpha coefficients, and overall model fit, we tested convergent validity and discriminant validity.

Schumacker and Lomax (2004) recommended that the standardized factor loadings for individual items should not fall below 0.50. This threshold ensures adequate representation of the latent constructs. Items RA1, RA5, and CA2 were removed due to relatively low factor loadings or minor cross-loadings that negatively affected model fit. Their exclusion improved structural validity and overall model fit, in line with Segars (1997) and Schumacker & Lomax (2004). In this study, we measured the primary constructs using multi-item scales. Consequently, we need to guarantee that the data quality of the measurement outcomes is satisfactory so that it is possible to carry out meaningful analyses of that data. Before being used as a measure, the internal consistency of each dimension was proven using Cronbach's alpha reliability test (α). Cronbach's alpha coefficient ranges from 0 to 1; the higher the coefficient, the more reliable the measure. Internal consistency of the eight constructs was found using Cronbach's alpha coefficients, and they were above 0.80 (0.889 to 0.966), indicating excellent internal consistency (Table 2).

Composite reliability (CR) and average variance extracted (AVE) were used to find the convergent validity. As Fornell and Larcker (1981) proposed, we ensured that CR values were at least 0.70 and AVE values exceeded 0.50. In this study, all eight constructs met these criteria (Table 2). Regarding discriminant validity (Chin, 1998), the square root of the AVE for each construct must surpass the correlation coefficients that define the construct and all the remaining ones. The measurement model fulfilled this criterion, thereby indicating satisfactory discriminant validity.

In this study, we adopted the criterion for an acceptable level of the chi-square to degrees of freedom ratio ($\chi^2/df < 5$), as recommended by Hair et al. (2009). Additionally, we used the criteria proposed by Hu and Bentler (1999) and Bagozzi and Yi (1988) to evaluate the fit of the measurement model. The results indicate that the model fit is satisfactory. Specifically, the chi-square to degrees of freedom ratio ($\chi^2/df = 3.149$) is within the acceptable range. The Normed Fit Index (NFI = 0.926), the Incremental Fit Index (IFI = 0.949), the Tucker-Lewis Index (TLI = 0.941), and the Comparative Fit Index (CFI = 0.948) all exceed or approach the commonly accepted threshold of 0.95. This is a good fit of the model to the data. Additionally, the Root Mean Square Error of Approximation (RMSEA = 0.075) provides somewhat higher than some common recommended cutoffs but is still consistent with the model being appropriate. The AVE values for all latent constructs exceed the recommended threshold of 0.50, which supports adequate convergent validity (Fornell & Larcker, 1981; Hair et al., 2009). In addition, the square roots of the AVE values, displayed in bold along the diagonal in Table 3, are consistently greater than the corresponding inter-construct correlation coefficients. This indicates that each construct shares more variance with its indicators than with other constructs, suggesting acceptable discriminant validity（Chin, 1998).

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Table 2 Results of construct validity and reliability analysis

construct	item	Mean	Std. Dev	factor loadings	α	CR	AVE
Relative Advantage	RA2	7.658	1.999	.897	.889	.923	.920
	RA3			.944			
	RA4			.923			
	RA7			.567			
Complexity	CL1	7.081	2.147	.888	.948	.876	.885
	CL2			.896			
	CL3			.918			
	CL4			.923			
Compatibility	CA1	7.241	2.084	.881	.953	.925	.921
	CA3			.942			
	CA4			.923			
	CA5			.920			
	CA6			.834			
Performance Expectancy	PE1	7.213	2.150	.889	.915	.920	.935
	PE2			.876			
	PE4			.885			
Effort Expectancy	EE1	7.429	2.098	.925	.930	.899	.920
	EE2			.867			
	EE3			.925			
Social Influence	SI1	7.449	2.087	.920	.950	.949	.823
	SI2			.848			
	SI5			.937			
	SI7			.922			
Individual Innovation	IN1	7.645	2.049	.916	.966	.967	.852
	IN2			.920			
	IN3			.935			
	IN5			.946			
	IN7			.899			
Use and Diffusion	UD1	7.700	2.122	.921	.940	.937	.922
	UD2			.913			
	UD3			.915			

Table 3 Results of discriminate validity

	RA	CL	CA	PE	EE	SI	IN	UD
RA	**0.959**							

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CL	.702**	**0.941**						
CA	.826**	.736**	**0.960**					
PE	.792**	.652**	.884**	**0.967**				
EE	.802**	.671**	.893**	.903**	**0.959**			
SI	.791**	.618**	.876**	.885**	.926**	**0.907**		
IN	.732**	.552**	.809**	.818**	.874**	.904**	**0.923**	
UD	.781**	.552**	.825**	.816**	.874**	.903**	.916**	**0.960**

**. Significant correlation at the 0.01 level (two-tailed).

5.2. Results of structural equation modeling

The significant correlations among relative advantage (RA), complexity (CL), compatibility (CA), performance expectancy (PE), effort expectancy (EE), social influence (SI), individual innovation (IN), and use and diffusion (UD) suggest that these variables are highly interconnected. Structural equation modeling (SEM) was used to uncover the structural relations among all the variables and to discriminate the relevance of each path. The analysis calculated the non-standardized coefficient (B), the standardized coefficient (β), the standard error (SE), the t-value, and R^2 (the explanatory power of independent variables) to test the hypotheses rigorously. The results indicated that nine out of ten hypotheses were supported (Table 4 and Figure 2). The relative advantage (RA) of AIGC significantly and positively influenced college students' performance expectancy ($\beta = 0.157$, $p = 0.002$) and effort expectancy ($\beta = 0.188$, $p < 0.001$) when utilized for design learning, thereby supporting Hypotheses 1 and 2, respectively. Conversely, the complexity (CL) of AIGC technology had a significantly negative impact on college students' performance expectancy($\beta = -0.090$, $p= 0.022$) and effort expectancy ($\beta = -0.103$,$p = 0.005$), aligning with Hypotheses 3 and 4. Furthermore, the compatibility (CA) of AIGC technology significantly and positively influenced college students' performance expectancy($\beta = 0.891$,$p < 0.001$) and effort expectancy ($\beta = 0.871$,$p < 0.001$) when employed for design learning, thus corroborating Hypotheses 5 and 6. Additionally, college students' effort expectancy of using AIGC technology for design learning significantly and positively influenced their continuous use of AIGC technology for design learning and its promotion and diffusion ($\beta = 0.361$,$p < 0.001$), supporting hypothesis 8. Social influence ($\beta = 0.409$,$p < 0.001$) and individual innovation ($\beta = 0.530$,$p < 0.001$) also significantly and positively influenced college students' continuous use of AIGC technology for design learning and its promotion and diffusion, thereby affirming hypotheses 9 and 10. However, no direct and significant impact was observed for college students' performance expectancy of using AIGC technology for design learning ($\beta = -0.110$,$p = 0.172$), leading to the rejection of hypothesis 7. The verified research structural model is shown in Fig. 2.

Table 4 Results of hypothesis test

Hypotheses	Hypothesized path	B	β	S. E	t	Result
H1	RA → PE	.16	.157	.052	3.088**	Supported
H2	RA → EE	.195	.188	.049	3.954***	Supported

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H3	CL → PE	-.086	-.090	.037	-2.299*	Supported
H4	CL → EE	-.099	-.103	.035	-2.801**	Supported
H5	CA → PE	.906	.891	.066	13.622***	Supported
H6	CA → EE	.897	.871	.063	14.279***	Supported
H7	PE → UD	-.093	-.110	.068	-1.365	Rejected
H8	EE → UD	.302	.361	.068	4.452***	Supported
H9	SI → UD	.362	.409	.091	3.965***	Supported
H10	IN → UD	.446	.530	.087	5.129***	Supported

*** P<.001 ** P<.005 * P<.05

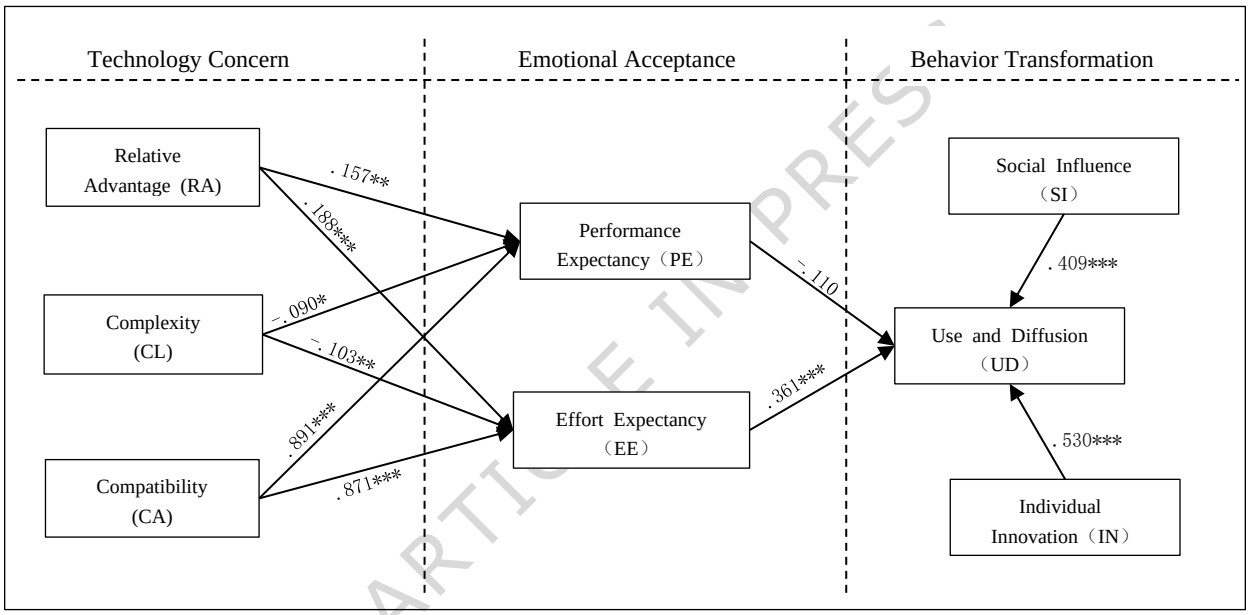

Fig. 2. The research model with its standardized coefficients. *** P<.001** P<. 005* P<.05

6. Discussion

This study investigates the relationship between AIGC technology characteristics and their adoption and diffusion among college students, using the AIDUA three-stage evaluation model in conjunction with the IDT. This approach integrates AIDUA and IDT to provide unique insights. Important factors influencing college students' attention to AIGC are relative advantage, complexity, and compatibility. Moreover, social influence and individual innovation are considered direct outcome variables, reflecting their effects at different stages. However, these factors interact across the dimensions of technology concern, emotional acceptance, and behavior transformation to influence college students' decisions. This study draws its conclusions through a systematic procedure that includes a literature review, questionnaire design, data collection, statistical analysis, model fitting, and hypothesis testing.

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6.1. The first-stage assessment

The first stage is the Technology Concern stage. This stage encompasses three variables: relative advantage, complexity, and compatibility. The findings suggest that the relative advantage and compatibility of AIGC have significant and positive impacts on both performance expectancy and effort expectancy. This is consistent with the results of Venkatesh et al. (2003) and Yang et al. (2024). The results show that technological advantages and strong compatibility can directly influence the positive experiences of college students when using AIGC. Specifically, relative advantage has positively correlated significantly with performance expectancy (0.157**) and effort expectancy (0.189***), with positive standardized coefficients. When college students perceive AIGC technology to have relative advantages, it more positively influences their expectations of achieving good performance by using the technology and their belief that the effort invested in it is worthwhile. This is because when AIGC demonstrates advantages such as being more efficient and creative compared to traditional design learning methods, students naturally have positive expectations regarding its performance and the return on their efforts.

Specifically, relative advantage is positively correlated with performance expectancy (0.157**) and effort expectancy (0.189***). When college students perceive AIGC technology as advantageous, they are more likely to expect to achieve good performance and believe in the worth of their efforts. High levels of compatibility enable students to integrate the new technology into their learning more efficiently, thus making more favorable judgments on learning effectiveness and the value of their efforts. The study further confirms that the relative advantage and compatibility of AIGC significantly enhance both performance expectancy and effort expectancy.

However, it is noteworthy that the complexity manifested by some AIGC technologies during their iteration requires users to engage in continuous learning, which may reduce the performance expectancy and effort expectancy of some college students. Complexity has a negative relationship with performance expectancy and effort expectancy (-0.090* and -0.103**). When AIGC technology is perceived as complex, it lowers students' expectations regarding both performance and effort. Highly complex technologies are difficult for students to master, which may discourage them from putting in the effort to learn and use the technology effectively. Therefore, negative behaviors related to use and diffusion may occur. Concerns about technological iteration may also limit their willingness to use and spread the technology.

AIGC technology offers several advantages, including high efficiency and creativity. However, students may not fully recognize these advantages due to limited understanding. Some students may be accustomed to traditional design learning methods and harbor cognitive biases towards the advantages of the new AIGC technology (Venkatesh et al., 2003). AIGC technology is highly professional and has a steep technical learning curve. Its operations and functions can be complex for college students without a technical background. Moreover, a lack of clear and accessible teaching resources and guidance may leave students confused and struggling to master the technology

(Davis,1989). Students' existing learning habits and knowledge systems have been formed over a long period and have a certain degree of stability and tenacity. The introduction of AIGC technology may disrupt students' existing learning patterns. Schools and teachers may not have fully considered how to help students integrate this new technology into their current learning systems (Rogers,2003).

6.2. The second-stage assessment

The second stage of AIGC emotional acceptance mainly involves performance expectancy and effort expectancy, which are significant manifestations of students' emotional acceptance of AIGC.

The expected performance benefits brought about by the technology should positively impact use and diffusion, yet the results show the opposite. Performance expectancy has a negative relationship with use and diffusion (-0.110), although this is statistically insignificant. Unexpectedly, the non-significant effect of performance expectancy on use and diffusion (H7 rejected) can be attributed to contextual factors in students' actual learning experiences. Although students anticipated enhanced performance through AIGC, the practical complexity, lack of adequate technical guidance, and insufficient integration of AIGC into the existing evaluation systems may have prevented these positive expectations from translating into actual behavioral change. Furthermore, moderators such as perceived anxiety and voluntariness may explain the non-significant relationship. Students experiencing anxiety towards novel AIGC technologies or perceiving low voluntariness may perceive performance expectancy differently, reducing its direct impact on actual technology adoption and diffusion behaviors. This suggests that higher performance expectancy does not necessarily lead to increased use and diffusion of AIGC. If AIGC technology does not significantly enhance learning efficiency, it will not promote students' use and diffusion behaviors. Moreover, interactions with AIGC often fail to capture students' behaviors accurately. In this study, performance expectancy did not directly impact students' use and diffusion. Even though students expect that using this technology can bring better learning outcomes, actual behavior change is still influenced by other factors. Effort expectancy is positively related to the use and diffusion of AIGC (0.361***). This implies that students are more likely to use and spread AIGC when they find the effort invested in it worthwhile. The reason is that when students feel that the effort they put into using the new technology can yield corresponding rewards, they will be more motivated to take actual actions.

Although students expect to perform well through AIGC technology, other more influential factors may impede them from translating this expectation into actual usage and diffusion behaviors. For instance, social and environmental factors may interfere with students' behavioral decisions. Even if students believe that technology can improve performance, if their classmates or teachers hold a conservative attitude toward it, it may affect students' actions (Ajzen,1991). Additionally, personal habits and attitudes may also play a crucial role. Some students may be unwilling to change, even if they see the new technology's performance advantages over traditional design methods (Fishbein & Ajzen, 1975).

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The positive association between students' effort expectancy and their practical use and diffusion behaviors suggests that their perceived effort is closely linked to their willingness to engage with technology. If students believe their efforts are not rewarded, they may reduce their willingness to use and diffuse the technology. The current teaching and evaluation systems often fail to reflect the value of students' efforts with AIGC. When students face difficulties, they often lack adequate support and guidance, leading them to feel that their efforts are wasted (Venkatesh et al.,2003). Our findings align with recent studies such as Huang et al. (2024) and Li (2024), who similarly reported the significant negative impact of complexity and positive impact of effort expectancy on the adoption of AI in educational contexts. Meanwhile, contrasting results regarding performance expectancy emphasize the necessity for deeper exploration into context-specific and discipline-specific moderators.

6.3. The third-stage assessment

The third stage, the behavior transformation, involves social influence and individual innovation, directly affecting students' adoption and dissemination of AIGC.

Effort expectancy associated with the technology significantly influences use and diffusion behaviors. Social influence has a significant positive association with use and diffusion (0.409***). This positive relationship between students' effort expectancy and their actual use and diffusion behaviors suggests that students' perceived effort is tied to their motivation to engage with the technology. If students believe their efforts are not rewarded, they may diminish their inclination to use and diffuse the technology. The surrounding social environment partly influences this reluctance during their learning process. People around them are more likely to follow suit when they use or recommend a particular technology. Individual innovation also has a significant positive correlation with use and diffusion (0.530***). This indicates that students with high individual innovation traits are more willing to use and diffuse AIGC. Such students tend to have a strong desire to explore and experiment with innovations, making them more likely to adopt and disseminate AIGC technology in design learning.

The study suggests that these results may be because, during the learning interaction process, this factor becomes a primary criterion for college students to evaluate their continued use of AIGC and its dissemination to others. Similarly, the performance expectancy demonstrated by AIGC technology shows no significant effect on use and diffusion. This could be because, during the college students' learning process, many students struggle to assess and accurately realize the benefits of the technology. College students are part of socially active groups, where the surrounding social circles strongly influence their learning behaviors and decisions. When classmates and teachers rarely use or recommend AIGC technology, it may lead to limited opportunities for some students to know about and access the technology, thus affecting their willingness to use and diffuse it. Moreover, in the absence of a campus environment that encourages the use of AIGC technology, students will struggle

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to perceive its practicality and appeal. This lack of exposure may discourage them from adopting the technology (Deutsch & Gerard, 1955).

Positive social influence and individual innovation significantly enhance college students' persuasiveness in using AIGC technology, indicating that the positive usage behaviors of others easily influence users. Meanwhile, when faced with an individual's proactive, innovative ability, college students tend to consider it a positive method for acquiring technology.

Nevertheless, not all students have incredibly high levels of individual innovation. Traditional educational models have influenced many students to adopt conservative learning and thinking patterns. Their willingness to experiment with and explore new things is reduced. Moreover, schools may fall short in fostering innovative capabilities in students. This fails to develop students' innovative potential fully. Therefore, the number of students with high individual innovation relatively is quite tiny (Amabile,1983). Nevertheless, the variability in students' innovative tendencies highlights the need for educators and policymakers to proactively foster innovative thinking and create supportive educational environments to maximize the adoption and benefits of AIGC technologies.

7. Implications, Limitations, and Future Research

7.1. Theoretical implications

From a theoretical perspective, the present study makes three contributions. First, scholars often concentrated on the instrumental value of AIGC regarding the perception of its persuasiveness in a specific context or towards a specific audience. However, most of them have overlooked the interaction between AIGC and users. This study is grounded in AIGC technology and IDT. It focuses on three prominent characteristics: relative advantage, complexity, and compatibility. Second, performance expectancy and effort expectancy are incorporated as mediating variables. Social influence and individual innovation were also included as theoretical supplements to validate the positive impact. The results indicate that college students' performance expectancy and effort expectancy have distinct impacts on the continuous use of AIGC and its diffusion. This implies that further research should specifically focus on the differential effects of various forms of performance expectancy on use and diffusion. Third, this study verifies the feasibility of the AIUDA model on the use and diffusion of AIGC among college students. This study categorizes college students' design learning with AIGC into three key evaluation stages. This provides new insights into how the innovation diffusion of new technology affects college students' perceptions of AIGC characteristics. It offers novel contributions to IDT by encouraging subsequent researchers to address technological characteristics, especially the negative impacts of complexity, to refine existing models.

7.2. Practical implications

Practically speaking, the research results offer certain practical implications. First, design quality can be improved by increasing efficiency, reducing complexity, enhancing compatibility, and offering personalized services. These improvements also facilitate the integration of interdisciplinary approaches and drive changes in design education. Second, tiered teaching resources need to be created that meet the different technical background needs of students. These resources may include online tutorials, video courses, and advanced modules tailored to different proficiency levels.

In addition, it is also important to provide timely technical support and organize Q&A sessions. At the same time, software developers should focus on designing the features and processes related to the operation interface on AIGC tools according to the needs of college students. This optimization aims to simplify tools, enhance usability, and create an environment that fosters active AIGC use, thereby minimizing the adverse effects of social and environmental factors on student behavior. Timely feedback and guidance are also essential, the amount of which allows students to know that their efforts are acknowledged and supported. Such an approach fits with the importance of formative assessment in the development of students. Third, we should clarify the use and the objectives of AIGC at different learning stages. On the technical level, we could formulate technical support and update strategies to ensure the adaptability of AIGC. Regular sharing sessions and result displays demonstrate AIGC's practical use and advantages in design learning to encourage more students to adopt and spread the technology. Students should also be encouraged to participate in scientific research projects and innovative practices, providing them with platforms to showcase their creative abilities. This can further stimulate innovation, motivation, and increase the proportion of students with high individual innovation characteristics.

Regarding practical application, further research should focus on the operational complexity of new technologies and their ease of use, enabling AIGC to support current design practices better. To practically reduce the complexity of AIGC integration in design curricula, educators should develop structured and staged curricula that introduce AIGC gradually, provide explicit instructional materials tailored to different competency levels, and offer accessible technological support platforms. Additionally, students could benefit from structured peer-learning environments where innovative users mentor less confident peers. For policymakers, establishing guidelines that mandate the inclusion of clear, step-by-step AIGC operation instructions and user-friendly interfaces in educational AI tools can significantly improve technology adoption and reduce perceived complexity among students. Meanwhile, equal attention should be paid to potential problems and countermeasures during the innovation diffusion process.

7.3. Limitations and future research

This study does have certain limitations. We gathered data via an online survey from design students in China, which restricts the generalizability of the results to other disciplines and cultural contexts. While the sample includes multiple universities, the findings may reflect culturally specific patterns that may differ in other educational systems. Therefore, future cross-cultural comparisons

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are recommended to examine the applicability of the model across diverse settings. Additionally, this study relied on self-reported data, which may introduce potential biases such as social desirability or response distortion. Although we ensured anonymity and used validated instruments to mitigate these risks, future research could adopt alternative methods, such as behavioral tracking or instructor evaluations, to enhance data robustness. Finally, due to the cross-sectional nature of the study, causal inferences cannot be made with certainty. Future investigations are encouraged to use longitudinal or experimental designs to capture the dynamic evolution of students' attitudes and behaviors toward AIGC technologies.

8. Conclusion

In this study, we surveyed undergraduate design majors to explore their behavioral intentions toward AIGC and the influencing factors, and proposed 10 research hypotheses. The data analysis results indicated that relative advantage and compatibility exert a significant positive predictive effect on students' performance expectancy and effort expectancy. Social influence and individual innovation can positively enhance college students' intentions to adopt and disseminate AIGC. However, technology complexity has a significant negative impact on both performance expectancy and effort expectancy, and can trigger negative emotions such as frustration and anxiety. These emotions may further hinder the positive effect of performance expectancy on behavioral change and on the effective use and diffusion of AIGC among college students.

In conclusion, this study proposed and empirically tested an integrated model to interpret college students' intention to use AIGC in design learning. By integrating the core perspectives of the AIDUA framework and IDT, the model demonstrated a good fit with the research context. It is important to note that this study does not claim full theoretical validation but provides preliminary empirical support for the applicability of these theoretical frameworks in the specific scenario of AIGC adoption among undergraduate design students. SEM - based empirical analysis revealed that relative advantage, technology complexity, compatibility, performance expectancy, effort expectancy, social influence, and individual innovation are key constructs for explaining college students' behavioral intentions and usage patterns regarding AIGC in design learning. This research contributes to the understanding of AIGC adoption in design education contexts and extends the application boundaries of the AIDUA framework and IDT to the empirical investigation of emerging intelligent technology adoption in educational settings. While this study offers empirical insights into AIGC adoption in design learning, its findings should be interpreted with caution, given several methodological and contextual limitations discussed earlier. Future research may further extend this work by expanding samples, employing multi-method approaches, and integrating institutional or pedagogical variables to deepen understanding of AIGC integration in educational contexts.

Data availability

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

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Author contributions

Li Zeng: Conceptualization, Investigation, Writing – original draft, Writing – review and editing; Aihong Wang: Data curation, Investigation, Formal analysis; Yaowu Huang: Investigation, Writing – review and editing; Yu Shen: Investigation, Writing – original draft. All authors reviewed the manuscript.

Funding: This work was supported by the National Social Science Fund of China (Project No.23BG129); Hunan Provincial Philosophy and Social Science Fund Project (Project No.22YBA327); Hunan Provincial Department of Education Research Project (Project No.24C0839); Hunan Vocational and Adult Education Society Planning Project (Project No. XH2024168); Key Project of Provincial-Level Teaching Reform for Undergraduate Education in the Second Batch of Zhejiang Province's 14th Five-Year Plan (Project No. JGZD2024097).

Competing interests

The authors declare no competing interests.

Ethical approval

Ethical approval for this study was granted an exemption by the Research Ethics Committee of J ingdezhen Ceramic University (JDCU-REC) (Exemption Number: JDTCU-EC-2024-048; Date: Oct ober 27, 2024). The exemption is justified as the research constitutes non-interventional social-be havioral research involving minimal risk, involving no physical procedures or collection of sensiti ve personal identifiers, in accordance with Article 31, Paragraph 1 of the "Measures for the Eth ical Review of Life Sciences and Medical Research Involving Human Beings" (National Health Commission [2023] No. 4). All procedures performed in this study were in accordance with the ethical standards of the 1964 Declaration of Helsinki and its later amendments.

Informed consent

Informed consent was obtained from all individual participants included in the study prior to data collection (between October 30 and November 30, 2024). For participants in the online survey, consent was obtained electronically by requiring them to read a detailed information page (covering research purposes, data usage, anonymity guarantees, and the right to withdraw) and then click an "Agree and Continue" button to proceed. For participants in offline interviews or paper-based surveys, written informed consent was obtained via signed consent forms. No minors or other vulnerable groups were included in the study sample.