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Factors Influencing University Students' Behavioral Intention to Use Generative Artificial Intelligence: Integrating the Theory of Planned Behavior and AI Literacy

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ABSTRACT

Generative artificial intelligence (GAI) advancements have ignited new expectations for artificial intelligence (AI)-enabled educational transformations. Based on the theory of planned behavior (TPB), this study combines structural equation modeling and interviews to analyze the influencing factors of Chinese university students' GAI technology usage intention. Regarding AI literacy, students' cognitive literacy in AI ethics scored the highest ($M = 5.740$), while AI awareness literacy scored the lowest ($M = 4.578$). Students' attitudes toward GAI significantly and positively influenced their usage intention, with the combined TPB framework and AI literacy explaining 59.3% of the variance. AI literacy and subjective norms positively influenced students' attitudes toward GAI technology and perceived behavioral control, and attitude mediated the impact of AI literacy and subjective norms on GAI usage intention. Further, the interviews provide new insights for university management and educational leadership regarding the construction of an educational ecosystem under the application of GAI technology.

KEYWORDS
AI literacy; behavioral intention; generative artificial intelligence; structural equation model; theory of planned behavior

1. Introduction

The rapid development of artificial intelligence (AI) has empowered numerous disciplines, including education, and the emergence of generative artificial intelligence (GAI) technology, such as ChatGPT and Sora, has attracted significant interest from international organizations and academia in the education sector (Chen et al., 2024). As a representative product of GAI technology, ChatGPT excels in multimodal user interactions alongside code and text analysis and generation. It enables personalized tutoring, real-time feedback, and enhanced learning experiences across various subjects (Hadi Mogavi et al., 2024; Obenza et al., 2024). Meanwhile, Sora specializes in high-quality and video production, which can be used for creating interactive educational content and virtual classrooms. Both models exemplify the transformative potential of GAI technology in education by reshaping the logic of educational resource creation and dissemination, altering teachers' roles, and redefining educational objectives (Abbas et al., 2024; Chan & Hu, 2023).

International organizations have also partaken in this trend. The World Intellectual Property Organization (WIPO, 2019) provided a clear definition of GAI technology and highlighted its significance across various societal domains, including education. The United Nations Educational, Scientific, and Cultural Organization (UNESCO, 2022, 2023) also issued several documents and reports guiding the proper application of AI-related technology in education that detailed the current application status, evolutionary trends, and development processes in the artificial intelligence in education (AIED) field, and outlined the future and significance of GAI technology for the education sector. Following the release of ChatGPT, UNESCO (2023) promptly issued the "Higher Education Action Guide for the GAI Era" to promote the rational and compliant application of emerging GAI technology in the education sector.

While important international organizations in the education sector have shown great interest in AI-enabled education, many researchers in the education field are actively engaged in research on AI- and GAI-technology-empowered education. Consequently, AI and GAI technology has made remarkable strides in various specific educational domains, including engineering (Khan et al., 2024), language (Cai et al., 2023; Chen et al., 2023; Liang et al., 2023), programming (Jing et al., 2024; Yilmaz & Yilmaz, 2023b), online learning (Hwang et al., 2021), intelligent learning (Chen et al., 2021), medical education (Winkler-Schwartz et al., 2019; Zhang et al., 2024), higher education (Bond et al., 2024), and e-learning (Tang et al., 2023). In the higher education context, universities are typically among the first to embrace emerging technology. Therefore, university students, who are deeply influenced by

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the development of information and communication technology (ICT), represent the demographic who have the most opportunity to engage in GAI technology (Alajmi et al., 2020; Bates et al., 2020; Chen et al., 2024). Education practitioners have also recognized the successful application of AI technology (especially GAI) in specific educational research fields. Specifically, GAI plays a unique role in the education process, including learning, assessment, teaching, testing, and management, thus impacting and even transforming every aspect of education. Overall, the trend toward GAI-empowering future education is unstoppable (Wang et al., 2024).

Understanding the disruptive impact of GAI on the education sector requires a comparison of traditional AI and GAI technology to gain deeper insights into the characteristics and capabilities of GAI technology for educational application (Kooli & Yusuf, 2024). Traditional AI-based applications and educational products typically employ rule-based and pattern-matching approaches, with the analysis and pattern recognition of large datasets at the core. These applications rely on predefined algorithms and rule sets to analyze the input data, generate results, or perform specific tasks. For example, in the education field, traditional AI applications may include intelligent educational software based on machine learning algorithms, recommendation systems for personalized learning paths, and automated student assessment tools. Although these applications can effectively process large amounts of data and provide useful outcomes, they often lack creativity and personalization (Onesi-Ozigagun et al., 2024).

Conversely, GAI technology focuses more on the creative generation of new content and information. This tool analyzes and understands input data and also generates new data, text, and images (Cong-Lem et al., 2024). A notable feature of GAI tools is their ability to produce content without explicit or predefined patterns. For example, ChatGPT is a GAI tool that can automatically generate coherent text based on user input, simulating a real conversation. Sora can generate video-teaching resources according to the needs of students or teachers. Therefore, in the education field, GAI tools can be used to creatively design instructional content, generate personalized learning materials, and provide intelligent tutoring and feedback based on natural language (Chen et al., 2024). These tools offer greater flexibility and creativity, enabling a richer and more personalized learning experience.

Owing to its qualitative transformation at the technical level, GAI technology has outstanding performance and can potentially meet the future needs of education. For example, it can empower intelligent tutoring systems to bring true personalized adaptive learning (Vujinović et al., 2024), and can also develop into physically intelligent learning companions and construct a new form of companion-based education. Therefore, it is highly anticipated by academics and is considered a key technology for transforming contemporary education.

Before the emergence of GAI technology, AI technology had already been applied in the education and related fields, leading to much research on the intention to accept AI technology (Chai et al., 2021; Yu et al., 2023; Zhang et al., 2024). For example, Chai et al. (2021) explore primary school students' attitudes toward learning about AI. Schiavo et al. (2024) examine how individuals' acceptance attitudes toward AI technology are influenced by their understanding and ability to use AI technology and their anxiety about its potential impacts. Through structural equation modeling (SEM), they find that individuals' technical literacy can promote positive acceptance attitudes toward AI technology, but anxiety affects acceptance attitudes to some extent. This suggests that when borrowing mature theories from the information management field, users' individual factors (i.e., literacy) should also be considered.

Several recent studies on the acceptance intention of GAI technology have emerged (Foroughi et al., 2023; Strzelecki, 2023). For example, Ivanov et al. (2024) use the theory of planned behavior (TPB) to explore the relationship between perceived benefits, advantages, disadvantages, and risks of GAI tools and individuals' attitudes, subjective norms, and perceived behavioral control. They reveal that perceived advantages toward and benefits of GAI technology positively impact acceptance attitudes, subjective norms, and perceived behavioral control, which, in turn, influence GAI adoption intention. However, the study overlooks individuals' ability to use GAI technology. As a cutting-edge technology, it is essential to understand the basic principles of GAI and successfully apply them to solve specific practical problems. Therefore, this study combines the research by Ivanov et al. (2024) and Schiavo et al. (2024) to explore the current status, reasons, and mechanisms of learners' intention to use GAI technology from the social (i.e., TPB) and individual (i.e., individual literacy) perspectives.

Another important reason for conducting this study is that, despite the substantial recognition of the empowering value of AI technology in education, its actual application in the teaching context remains limited (Jing et al., 2024). Overcoming the inertia of educational system reforms and understanding university students' expectations regarding the application of GAI in education and teaching are pressing issues in the current research. This study aims to address this research gap by integrating SEM and interviews to understand university students' subjective attitudes and behavioral intention regarding GAI technology. The goal is to provide recommendations and guidance for current educational practices that utilize GAI technology and promote the reasonable and positive development of the AIED research. Therefore, using the AI literacy and TPB concepts, this study constructs a SEM to understand university students' AI literacy levels and the factors influencing their behavioral intention to use GAI technology. This study then uses grounded theory to gain insights into the quantitative analysis results. The research questions (RQ) are as follows:

RQ1: What is the overall state of AI literacy among university students in Zhejiang Province?

RQ2: To what extent can the AI literacy and TPB concepts explain students' behavioral intention to use GAI technology?

RQ3: What are the key factors influencing students' behavioral intention to use GAI technology?

RQ4: Do attitudes and perceived behavioral control play mediating roles in the model? If there is a mediating effect, what type of mediation is involved?

2. Literature review and hypotheses development

Once novel technology is integrated into educational settings, scholars frequently focus on the extent to which it is used by university students and teachers (Dai et al., 2024). This emphasis stems from the implications it holds for its potential transformative impact on current teaching and learning methodologies. As an example of contemporary innovation, GAI technology is subject to scrutiny. University students' reception of and propensity to employ GAI technology are intricately tied to its broad implementation and deployment.

2.1. Theoretical background

Emerging technology has significantly affected the education field, with numerous mature theories and analytical frameworks established to study individuals' acceptance and intention usage (Dai et al., 2024). For example, Lin (2012) utilized task-technology fit (TTF) theory to explore factors influencing students' intention to continue using virtual learning systems. Similarly, Bazelais et al. (2017) apply the technology acceptance model (TAM) to analyze university students' behavioral intention to use online learning technology. More recently, Wang et al. (2023) combine the TTF and TAM perspectives to investigate university students' behavioral intention to use new online learning spaces, such as BiliBili and YouTube. Other frameworks, such as the information system success model (Yang et al., 2017), expectation confirmation theory (Tawafak et al., 2021), and the unified theory of acceptance and use of technology (Chu & Dai, 2021; Foroughi et al., 2023; Strzelecki, 2023) have been successfully applied to examine the factors that influence university students' intention to use new technology in education.

GAI technology has profoundly transformed the current state of education, compelling the educational system to undergo reform (Çelebi et al., 2023; Chen et al., 2024; Yilmaz & Yilmaz 2023a). Learners, the first to embrace emerging GAI technology, play a crucial role in driving this reform. Therefore, it is important to explore learners' attitudes and adoption intention toward GAI as a new productive force. Wang et al. (2023) assert that when analyzing such learners, they should be placed in a specific social context that focuses on their social exposure and the era in which they have grown up. Considering these factors, the TPB is a highly appropriate theoretical framework for the current study.

The TPB, derived from rational action theory (Ajzen, 1985), is a well-established framework that can be used to explain university students' behavioral intention to use new technology (Fishbein & Ajzen, 1975; Hamad et al., 2024; Madden et al., 1992). Fishbein and Ajzen (2010) conceptualized human behavior as a series of rational acts that follow behavioral intention and identified three key influencing factors: subjective norms, attitudes, and perceived behavioral control. According to the TPB, individuals are more likely to engage in a behavior if it is expected to produce positive outcomes (attitude), is perceived as normative and socially acceptable (subjective norms), and is seen as controllable with expected outcomes (perceived behavioral control) (Hamad et al., 2024; Van Lange et al., 2011).

The TPB provides a clear and concise framework (see Figure 1) for explaining human behavioral intention, offering an abstract yet practical perspective on human decision-making. This theory has been widely applied in fields such as social services and healthcare. For example, Hyde and Knowles (2013) found that the TPB could effectively explain Australian university students' behavioral intention to volunteer. In the education field, the TPB has been extensively used to effectively predict university students' behavioral intention (Cheon et al., 2012; Mei et al., 2017; Teo, 2012). Cheng et al. (2015) show that subjective norms and perceived behavioral control significantly influence university students' intention to engage in electronic collaboration. Cheon et al. (2012) and Arteaga Sánchez et al. (2013) use the TPB to explain university students' intention to adopt mobile learning technology and WebCT systems, respectively. The ongoing research continues to explore modifications and extensions of the TPB in the education field (Habibi et al., 2023; Ivanov et al., 2024; Yan et al., 2023).

Despite the extensive application of the TPB in education, its use in predicting university students' behavioral intention toward GAI in educational applications remains relatively underexplored. This represents a critical research gap because understanding the factors that influence students' intention to use GAI technology is essential for the effective integration of GAI technology into educational settings. This study addresses this gap by employing the TPB to investigate the factors that influence university students' behavioral intention to use GAI technology.

The significance of this research lies in its potential to broaden the application scope of the TPB and provide insights into the acceptance of GAI technology in education. By adopting a quantitative research approach, this study identifies key factors that influence university students' use of GAI technology, so as to assist in learning. Further, the qualitative interviews deconstruct the underlying mechanisms behind these

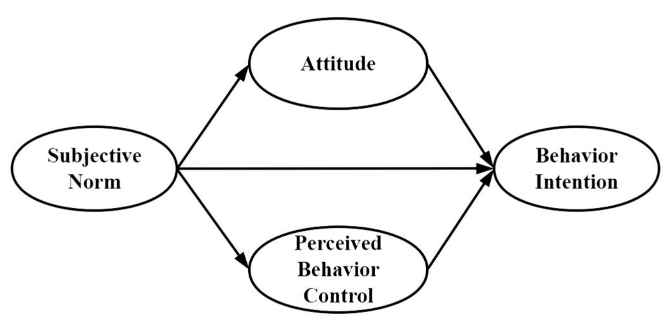

Figure 1. TPB theoretical model.

behaviors, offering evidence to support the quantitative findings and substantiate the SEM results. Ultimately, this study deepens the understanding of the application of GAI technology and its impact on university students, thereby contributing to the development of more effective educational strategies and policies.

2.2. Hypotheses development

The prior research has demonstrated the significance of the TPB as a fundamental theoretical framework for comprehending human behavior and devising strategies for behavioral interventions. However, in the context of the present research topic, a suitable adaptation of the TPB is required due to university students' heightened literacy levels regarding the application of GAI technology. Therefore, this study incorporates the AI literacy concept into the TPB, resulting in a logical and expanded model, as illustrated in Figure 2.

2.2.1. AI literacy

AI literacy is complex, especially given the rapid development of AI technology in recent years, which has often resulted in a lag in the evolution of literacy connotations. The extant research has revealed a lack of literacy scales specifically tailored to GAI (Çelebi et al., 2023). Therefore, this study modifies the extant AI literacy scales to fit the context in which GAI technology is applied. Several well-established concepts and corresponding scales for AI literacy exist. For example, Carolus et al.'s (2023) MAILS-Meta-AI literacy scale, which focuses on competency models, psychological changes, and meta-competencies. Similarly, Laupichler et al.'s (2023) scale for the assessment of non-experts' AI literacy uses an exploratory factor analysis approach. Ng et al. (2023) propose an AI literacy questionnaire that is validated through confirmatory factor analysis, and Hornberger et al. (2023) develop an AI literacy test to measure university students' AI knowledge. These scales each have their own emphasis, such as Hornberger et al. (2023), whose scale focuses more on assessing learners' AI knowledge, considering that the mastery of AI knowledge is an important component of AI literacy. These scales have significant value in specific contexts.

Building on the aforementioned studies, this study analyzes a series of AI literacy-related studies that focus on a subject's understanding, application, evaluation, and ethical awareness of AI technology (Calvani et al., 2009; Çelebi et al., 2023; Chai et al., 2020; Moore, 2010; Wang et al., 2023; Wilson et al., 2015). Accordingly, this study defines AI literacy to include the following competencies: a practical understanding of GAI technology; proficiency in its application for task completion; the ability to analyze, select, and critically evaluate AI-generated data and information; and awareness of the ethical and moral considerations associated with its use.

In the SEM research, a second-order variable constructed from several first-order variables is often used to represent complex concepts (Chin, 1998). Therefore, this study applies a four-dimensional conceptualization of AI literacy; that is, awareness, usage, evaluation, and ethics. These dimensions collectively constitute a higher-order latent variable within the theoretical model developed herein. The rationale for adopting this four-dimensional model is to capture a comprehensive understanding of AI literacy that transcends mere technical skills to include critical evaluations and ethical considerations.

The development of these concepts is inseparable from their empirical validation. The previous empirical analyses have examined various aspects of AI literacy, such as Chai et al. (2020), who use SEM to validate the influence of AI literacy on university students' attitudes toward AI learning. Chai et al. (2020) further argue that AI literacy serves as a fundamental basis for shaping individuals' behavioral, normative, and control beliefs, thereby positively affecting university students' intention to adopt GAI technology and

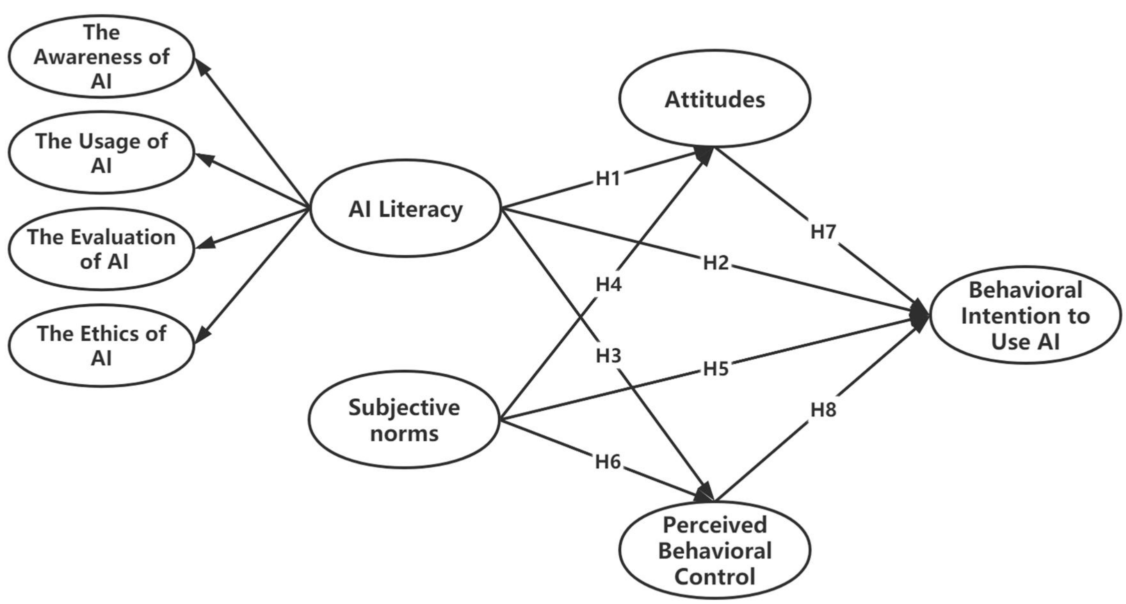

Figure 2. Theoretical model.

their perceived behavioral control. Similarly, studies in the education field have emphasized the importance of technology-related literacy (such as ICT literacy and digital literacy) in shaping university students' expectations and behavioral intention to use technological tools (Jong et al., 2018; Mac Callum et al., 2014; Mohammadyari & Singh, 2015). Based on the above, this study posits the following:

H1: AI literacy has a positive effect on attitudes toward GAI.
H2: AI literacy has a positive effect on behavioral intention to use GAI.
H3: AI literacy has a positive effect on perceived behavioral control.

2.2.2. Subjective norms

The subjective norm concept holds paramount importance within the TPB as it denotes an individual's perception of the influence exerted by social expectations and the opinions of others on their behavior (Ajzen, 1985). The previous research has consistently validated the relationships and mechanisms through which subjective norms impact attitudes and behavioral intention. For example, Otache (2019), who demonstrated the significant influence of subjective norms on behavioral intention in the context of entrepreneurial practices. Meanwhile, Meng and Choi (2019) established a notable impact on users' intention to utilize location-based services. Chai et al. (2020) also examine the effects of university students' subjective norms on their perceived attitudes and behavioral intention regarding technology usage, and reveal that positive social influences can enhance university students' attitudes and behavioral intention toward learning about GAI technology, which consequently bolsters their confidence in its utilization. Drawing on the above, this study posits the following:

H4: Subjective norms have a positive effect on attitudes toward GAI.
H5: Subjective norms have a positive effect on behavioral intention to use GAI.
H6: Subjective norms have a positive effect on perceived behavioral control.

2.2.3. Attitude

Attitude is an important variable that can predict university students' behavioral intention to use GAI technology in the TPB framework, specifically referring to university students' subjective emotional cognition toward AI technology or products, such as ChatGPT. Ajzen (1985) asserts that the more positive an individual's attitude, then the greater the support from significant others, the stronger the perceived behavioral control, and the greater the intention to act; conversely, the smaller their intention to act. Many scholars have empirically validated the influence of attitude on ultimate intention to act. For example, Han et al. (2010) reveal that customer attitudes toward green hotels positively influence their intention to book these hotels. In the education field, Valtonen et al. (2015) demonstrate through quasi-experimental research that teachers' attitudes toward ICT affect their behavioral intention to use ICT. Finally, Wang et al. (2022) use surveys to reveal that university students' subjective attitudes toward online learning environments are key determinants of their behavioral intention. Based on the above, this study posits the following:

H7: Attitude has a positive effect on behavioral intention to use GAI.

2.2.4. Perceived behavioral control

Perceived behavioral control encompasses an individual's beliefs and subjective assessments of their ability to exert control over a specific behavior. The TPB posits that a heightened perception of behavioral control corresponds to an increased inclination to engage in the intended behavior (Ajzen, 1985). In the education field, numerous scholars have underscored the noteworthy impact of perceived behavioral control on university students' intention to participate in online learning activities (Lung-Guang, 2019; Pan et al., 2023). This influential relationship remains valid when considering the promotion of educational technology (Arkorful et al., 2020; Sungur-Gül & Ateş, 2021). Consequently, it can be inferred that university students' attitudes toward the use of AI technology are aligned with this pattern. Based on the above, this study posits the following:

H8: Perceived behavioral control has a positive effect on behavioral intention to use GAI.

3. Methodology

3.1. Survey design

This study drew on well-established theoretical frameworks and concepts (the TPB and AI literacy) and utilized multiple questionnaires devised by scholars during the questionnaire development process. Specifically, to measure the four TPB variables (subjective norms, perceived behavioral control, attitudes, and behavioral intention to use AI) this study referred to the questionnaires by Ajzen (1985), Chai et al. (2020), Chai et al. (2021), Fishbein and Ajzen (2010), and Van Lange et al. (2011). To measure the four AI literacy aspects (awareness, usage, evaluation, and ethics of AI), this study referred to the questionnaires by Chai et al. (2020) and Wang et al. (2023). To construct the questionnaire, this study used that developed by Wang et al. (2023) as the foundation and supplemented it with several items from Chai et al.'s (2020) questionnaire to ensure that the AI literacy content was thoroughly represented.

To better align the questionnaire with this study's research context, adjustments were made based on actual scenarios, including university students' daily lives and learning environments as well as the development of GAI technology. For example, in the AI evaluation section, this study added specific GAI examples (such as ChatGPT and

Sora) to help the participants to better understand the items. Further, this study focused on the higher education context, emphasized the influence of teachers and peers in the subjective norms section, and narrowed the influential individuals or groups in the original questionnaires to specific groups of university students. Moreover, in the questionnaire sections on intention to use and perceived behavioral control, this study highlighted the specific use of GAI to assist in the completion of learning tasks. These adjustments ensured that the questionnaire accurately reflected the real experiences of the target population and was relevant to the research context.

Due to the lack of specific scales for GAI literacy, this study adapted the extant AI literacy scales to evaluate the university students' abilities to use and assess GAI. When adapting the questionnaire for contextual suitability, relevant items from the extant questionnaires were modified to align them with the research context; that is, the acceptance of GAI technology. However, some items, such as AWA2, were challenging to adapt to GAI-related scenarios. Nevertheless, these items were retained because they were distinctive and could measure the participants' ability to recognize AI in real-life situations. Considering the aforementioned factors, the final questionnaire used a combination of items that specifically mentioned GAI and more general AI application items.

Scholars in the SEM field have empirically demonstrated that larger-scale measurement instruments, such as a seven-point Likert scale, outperform smaller-scale instruments (e.g., four- and five-point Likert scales) in terms of enhancing reliability and validity (Brown, 2011; Dawes, 2002; Wang et al., 2023). However, it is essential to avoid excessive scale expansion without justification (Yusoff & Mohd Janor, 2014). Consequently, this study used a seven-point Likert scale to gauge the observed variables. Comprising 29 items, the questionnaire encompassed 8 latent variables, of which 4 constituted the second-order latent construct of "AI literacy." Each item was assessed using a seven-point Likert scale to ensure comprehensive measurement coverage.

The scale underwent an initial pilot test conducted by the research team and obtained 68 pilot data responses for the subsequent analysis (see Tables A1 and A2 for the pretest reliability and validity results). Following the analysis results, this study excluded two items (AWA1 and AWA3) that exhibited insufficient reliability and validity. The remaining four items were reordered from AWA1 to AWA4. Consequently, the revised questionnaire contained 27 items. To further enrich the questionnaire, four additional items (sex, educational stage, school name, and major) were incorporated (see Table A3 for the finalized version of the questionnaire).

3.2. Data collection: Questionnaire

The questionnaire was primarily distributed through the Wenjuanxing platform (https://www.wjx.cn/) from late September to mid-November of 2023. To ensure the integrity of the collected data, the time-tracking functionality of the Wenjuanxing platform was activated during the survey distribution process. Overall, 327 responses were gathered from university students enrolled in various universities in Zhejiang Province. Rigorous measures were undertaken to safeguard sample quality; these aligned with the methodological recommendations outlined by Hair et al. (2012), as follows. First, based on insights derived from the pilot test, the completion of the questionnaire typically required 2–5 min. Consequently, the participants who completed the questionnaire within a remarkably short duration (100 s) were considered to have approached the task irresponsibly, resulting in their data being classified as invalid. Second, a reversed item was included in the questionnaire. Participants who failed to respond accurately to this item had their data deemed invalid.

After rigorous selection, 82 invalid questionnaires were excluded. Among them, 32 questionnaires were discarded based on the insufficient response time, and 50 questionnaires were eliminated because of incorrect responses to the reversed item. Consequently, 245 valid questionnaires were retained for the formal data analysis, representing a valid response rate of 74.9%.

3.3. Data collection: Interviews

The interview and questionnaire data collection processes were conducted concurrently. A random sampling strategy was used to select 18 participants for the interviews. Among them, 15 had completed the questionnaire and agreed to participate in the interviews. To ensure the participants' cooperation during the interviews, compensation of RMB 30 was provided upon interview completion. The interviews followed the established guidelines for social science research (Lune & Berg, 2021; Nachmias et al., 2015). A semi-structured interview approach was used that was guided by a predetermined, open-ended interview outline (see Table A4 for additional information on the participants).

The interview protocol consisted of a set of key questions aimed at exploring various aspects of the participants' perspectives, such as: (1) How do individuals perceive the future prospects of AI development? (2) What are their attitudes toward the application of AI in educational settings, and what factors influence their decision-making processes concerning the adoption of AI in learning activities? (3) To what extent do individuals feel equipped to navigate the rapidly evolving landscape of AI technology and its associated applications? (4) What strategies should universities employ to facilitate the responsible and effective integration of AI technology into teaching practices? (5) What are the individuals' opinions on the emerging trends in GAI, specifically the use of AI-generated content? This study adhered to ethical guidelines (Lune & Berg, 2021) to ensure that participants were duly informed about the recording of the interviews, and that privacy safeguards were implemented throughout the interview process.

During the interview phase, the researchers actively pursued authentic and reflective information that captured the realities under investigation. To accomplish this objective, the participants were prompted to expand upon and clarify specific viewpoints that arose during the interviews. Further, to safeguard the genuineness and dependability of the data and minimize subjective bias, the researchers employed an iterative process of scrutinizing and augmenting the accumulated viewpoints. This process entailed cross-referencing the information provided by the participants with diverse perspectives to corroborate the findings. Each interview session lasted approximately 20-50 min. Upon interview completion, the text data were organized and analyzed. This data provided distinctive insights into the interpretation of the quantitative research outcomes.

3.4. Data analysis

3.4.1. Quantitative data analysis

The questionnaire data were analyzed using Amos (v26) and SPSS (v28). Amos, a data analysis tool based on covariance-based SEM (CB-SEM) that has numerous advantages, was used to statistically evaluate the proposed hypothetical model. CB-SEM, chosen over first-generation SEM techniques, such as partial least squares, was suitable for the data analysis because of its ability to generate synchronous relationships among the latent constructs (Hair et al., 2012). Among the available CB-SEM analysis software, Amos stands out for several reasons. First, it applies a covariance structure analysis to validate the hypothesized model and offers a user-friendly visual interface that effectively presents the SEM analysis results. Second, Amos incorporates the bootstrapping method, which plays a crucial role in deriving the necessary confidence intervals. The process of conducting visual data inspection and model analysis using Amos typically involves the following two-stage approach (Hair et al., 2010). First, it is essential to assess the reliability and validity of each latent variable, which involves scrutinizing the measurement model. This stage encompasses reliability and validity assessments and serves as the foundation for the subsequent analysis. Second, once the reliability and validity tests are satisfied, the model fit is examined to ensure that the analyzed paths accurately represent genuine relationships. Then, an in-depth analysis of the interrelationships among the different constructs is conducted, encompassing a systematic validation and mediation analysis of the structural model (Hair et al., 2012).

3.4.2. Text data analysis

The purpose of the text data analysis was to complement the interpretation of the quantitative data results. Therefore, the text data analysis was based on the conclusions drawn from the quantitative analysis with the aim of identifying possible causal explanations to elucidate the quantitative findings. While the quantitative analysis provided rigid results, the qualitative analysis allowed for flexible exploration, induction, and deconstruction. Understanding this characteristic helped to appreciate the value of the text data analysis.

NVivo (v12) was used to analyze the text data. The analysis focused on segments of the interviews (pertaining to the relationships between the variables in the SEM) to support and explain the results obtained from the quantitative research. The specific analysis procedure followed the text data analysis method based on grounded theory (Glaser & Strauss, 2017). However, because the interview analysis was not intended to generate theory, the main reference was the operational procedure of the first-level coding (open coding or open login) from the three-level coding of grounded theory. Relevant content mentioning related concepts was extracted and coded from the raw data.

During the data analysis, the researchers objectively and rationally extracted and explored important information and clues hidden in the data. Based on the methodological system of grounded theory, the open coding process saw the researchers suspend personal and subjective judgments and preconceived opinions on the research topic (Strauss & Corbin, 1990). Thereafter, the data were processed, and through a comparative analysis and integration of the text, similar concepts and viewpoints were summarized to explore the causal logic and underlying mechanisms of the relationships between the variables of interest while reading the interview text line by line.

During the open coding process, the results mainly served to support the quantitative results owing to the explicit purpose of the text analysis. Therefore, this study only borrowed the pattern of organizing, summarizing, and extracting text materials from open coding and identified valuable information during the coding process (see Table A5 for the coding table). The identified text data were used to increase the persuasiveness of the analysis and enhance the depth of the causal logic behind the structural model.

4. Results

4.1. Common method bias

The data were obtained from a single source (participants or interviewees) using a self-reported approach with a fixed-response format. However, this data collection method is susceptible to common method bias (CMB). CMB refers to the potential distortion caused by factors such as a shared measurement environment, item context, and item characteristics. Appropriate steps were taken to address the influence of CMB and minimize the artificial covariation between the predictor and criterion variables stemming from these shared factors (Podsakoff et al., 2003; Xia et al., 2024).

To address common method variance, it is crucial to employ procedural control methods that minimize the potential sources of bias. This study adhered to the protocols and statistical techniques proposed by Cham et al. (2020) and Podsakoff et al. (2012). During the data collection phase, a conscious effort was made to design questionnaire items related to different variables on separate pages, so as to provide the participants with ample time to rest between pages. This approach aimed to mitigate potential common method variance effects arising from the

Table 1. Demographic profile of the study participants.

Demographics	Classification	Number	Proportion (%)
Gender	Male	119	48.6
	Female	126	51.4
Level of Study	Freshman	3	1.2
	Sophomore	28	11.4
	Junior	56	22.9
	Senior	109	44.5
	Postgraduate	52	21.1
Study Discipline	Arts and humanities	59	24.0
	Social Sciences	40	16.3
	Natural Science	109	44.4
	Engineering	40	16.3

Table 2. Descriptive statistics of participants' AI literacy status.

Dimension	Item	Number	Mean	SE	Average Score (S)
Awareness of AI	AWA1	245	4.900	1.484	4.578
	AWA2	245	4.470	1.527	
	AWA3	245	4.510	1.636	
	AWA4	245	4.430	1.614	
Usage of AI	USE1	245	5.070	1.501	5.197
	USE2	245	5.170	1.368	
	USE3	245	5.350	1.369	
Evaluation of AI	EVA1	245	4.930	1.350	5.097
	EVA2	245	5.250	1.408	
	EVA3	245	5.110	1.331	
Ethics of AI	ETH1	245	5.940	1.296	5.740
	ETH2	245	5.890	1.299	
	ETH3	245	5.390	1.558	

continuous use of the same scale (Shiau et al., 2019). Further, Harman's single-factor test was used to conduct a principal component analysis and assess the presence of CMB. The analysis revealed that eight factors exhibited eigenvalues greater than 1, which was consistent with the initial model design. Moreover, based on the various indices derived from Harman's single-factor test, no substantial indications of significant CMB were observed among the variables (Hair et al., 2014; Malhotra et al., 2006), and the findings were within the acceptable ranges.

4.2. Demographic analysis

The participants' demographic information was analyzed using SPSS (Table 1). Overall, 245 valid questionnaire responses (119 males, 126 females)were obtained. This study included a comprehensive range of 25 universities situated within Zhejiang Province. Regarding participants' academic standing, the cohort consisted of 196 undergraduate and 52 graduate students, including individuals pursuing master's and doctoral degrees. Regarding the fields of study, humanities, social sciences, natural sciences, and engineering accounted for 59, 40, 109, and 40 of the participants, respectively. The distribution of the participants' demographic characteristics demonstrated a representative sample of the wider population.

The participants' proficiency in the four AI literacy dimensions was further analyzed (Table 2). The mean scores for the 13 items across the 4 dimensions were relatively high. However, owing to the absence of established norms for AI literacy in the extant research, determining the participants' relative levels of AI literacy remained inconclusive. Nevertheless, upon examining the different types of AI literacy within the participant groups, the highest mean score ($M = 5.740$) was observed for AI ethics, indicating a heightened awareness of ethical considerations regarding AI applications, such as potential data breaches. Conversely, the lowest mean score ($M = 4.578$) was for AI awareness. This may be attributed to the pervasive integration of AI technology into various aspects of daily life and learning, causing most participants to be unaware of the presence and underlying principles of this technology in their daily experiences.

4.3. Validity and reliability testing

Before conducting the SEM tests, the reliability (gauged through Cronbach's alpha coefficients using SPSS and composite reliability [CR]) and validity (via convergent and discriminant validity) were assessed. The results revealed that the Cronbach's alpha coefficients ranged from 0.789–0.924 for the constructs, which exceeded the 0.70 benchmark (Hair et al., 2014) and substantiated the questionnaire's reliability.

Relying exclusively on Cronbach's alphas to establish validity in a SEM falls short of providing a comprehensive evaluation. To assess the construct validity, two key indicators were carefully considered: CR and the average variance extracted (AVE). Conventionally, the reliability evaluation of individual items entails scrutinizing their factor loadings (Std. in Table 3). In SEM, the AVE and CR benchmarks are 0.50 (Fornell & Larcker, 1981) and 0.70 (Hair et al., 2011), respectively. In this study, all CR values exceeded 0.70, the AVE values exceeded 0.50, and the factor loadings exceeded 0.60, affirming a satisfactory level of internal consistency and acceptable reliability across the measured constructs (see Table 3 for the results).

Validity testing primarily examines the discriminant validity among variables, which refers to the low correlation and significant differences between latent variables. This can be evaluated by comparing the square root of the AVE with the correlation coefficients between the variables. Following Fornell and Larcker (1981), if the correlation coefficient between one variable and the other is smaller than the square root of the AVE, then that variable has good discriminant validity. In Table 4, the bold values represented the square root of the AVE, and the triangular values represented Pearson's correlation coefficients. The square root of the AVE was generally larger than all other values. Based on this observation, the measurement model had appropriate discriminant validity.

4.4. SEM fit indices

To ensure that the hypothesized relationships were not spurious, the SEM required a fit evaluation. Following Hair et al. (2012), this study evaluated the model fit indices (see Table 5). Referring to Yu et al. (2023), the model fit was assessed using the standards employed by Bagozzi and Yi (1988), Hair et al. (2017), Hayduk (1987), and Hu and Bentler (1998).

Table 3. The results of the reliability and convergent validity of the measurement model.

		Significance estimation							
Dimension	Items	Unstd.	S.E.	z-value	*p*-value	Std.	AVE	CR	Cronbach's alpha
Awareness of AI	AWA1	1.000				0.821	0.622	0.868	0.867
	AWA2	0.916	0.068	13.475	***	0.801			
	AWA3	0.832	0.068	12.315	***	0.744			
	AWA4	0.956	0.072	13.229	***	0.789			
Usage of AI	USE1	1.000				0.911	0.734	0.892	0.890
	USE2	0.949	0.051	18.576	***	0.865			
	USE3	0.955	0.060	15.866	***	0.791			
Evaluation of AI	EVA1	1.000				0.937	0.727	0.888	0.883
	EVA2	0.936	0.053	17.769	***	0.822			
	EVA3	0.864	0.052	16.577	***	0.793			
Ethics of AI	ETH1	1.000				0.651	0.594	0.811	0.789
	ETH2	1.146	0.113	10.153	***	0.894			
	ETH3	0.956	0.099	9.640	***	0.748			
Subjective Norms	SN1	1.000				0.838	0.661	0.886	0.886
	SN2	1.039	0.075	13.897	***	0.779			
	SN3	0.898	0.066	13.645	***	0.769			
	SN4	1.053	0.066	16.006	***	0.862			
Perceived Behavioral Control	PBC1	1.000				0.875	0.656	0.849	0.831
	PBC2	1.008	0.061	16.650	***	0.873			
	PBC3	0.896	0.078	11.435	***	0.664			
Attitudes	ATT1	1.000				0.852	0.716	0.909	0.907
	ATT2	1.079	0.060	18.010	***	0.888			
	ATT3	0.975	0.067	14.660	***	0.782			
	ATT4	1.002	0.059	17.033	***	0.858			
Behavioral Intention to Use AI	BI1	1.000				0.846	0.755	0.925	0.924
	BI2	1.148	0.071	16.077	***	0.828			
	BI3	1.148	0.062	18.552	***	0.901			
	BI4	1.062	0.057	18.480	***	0.899			

Note: *$^{***}p < 0.001$.*

Table 4. Discriminant validity.

		Discriminant validity							
	AVE	USE	ATT	PBC	BI	EVA	AWA	SN	ETH
USE	0.734	**0.857**							
ATT	0.716	0.574	**0.846**						
PBC	0.656	0.707	0.600	**0.810**					
BI	0.755	0.516	0.758	0.552	**0.869**				
EVA	0.727	0.780	0.615	0.675	0.525	**0.853**			
AWA	0.622	0.537	0.422	0.611	0.373	0.665	**0.789**		
SN	0.661	0.529	0.686	0.684	0.582	0.593	0.545	**0.813**	
ETH	0.594	0.542	0.519	0.527	0.497	0.560	0.338	0.538	**0.771**

Note: The bold numbers on the diagonal represent the root of AVE, and the lower triangle represents the Pearson correlation coefficient of the facet.

The model fit indices were calculated using Amos (v26.0); the corresponding numerical results and recommended values are shown in Table 5. The comparative analysis results revealed that all fit indices, except the goodness of fit, had favorable model fit within the acceptable range of 0.8–0.9, thus substantiating the model's appropriateness for accommodating the collected data and validating the interrelationships among the variables.

4.5. SEM validation

SEM validation assesses a model's explanatory capacity. This study employed Amos (v26.0) to compute the path coefficients and examine the variance explained by each variable (Figure 3). Notably, this study incorporated a second-order variable, AI literacy, necessitating an analysis of its constituent weights (Table 6).

To gain a clearer understanding of the model, this study assessed the strength of the relationships between different variables and validated the hypotheses. The model's path analysis results are presented in Table 7.

Of the eight hypotheses, five garnered support (Table 7). Notably, AI literacy ($\beta = 0.398$, $p < 0.001$) and subjective norms ($\beta = 0.416$, $p < 0.001$) exerted significant influence on university students' attitudes toward AI. It is crucial to interpret the meaning of the path coefficients (β) as they provide intuitive insight into the magnitude of intervariable influence. For instance, considering the path coefficient of AI literacy on attitudes toward AI ($\beta = 0.398$), a unit increase in university students' AI literacy led to a 0.398 unit increase in their attitudes toward GAI technology. Moreover, both AI literacy ($\beta = 0.623$, $p < 0.001$) and subjective norms ($\beta = 0.260$, $p < 0.001$) demonstrated substantial positive effects on university students' perceived behavioral control. However, when assessing their behavioral intention to use GAI technology, the students' attitudes toward AI emerged as a significant predictor variable ($\beta = 0.624$, $p < 0.001$). Consequently, this study accepts H1, H3, H4, H6, and H7, while H2, H5, and H8 fail to find support within the study confines.

Regarding the explained variance (explanatory power), the combined influence of AI literacy and subjective norms was responsible for 55.7% of the variance observed in the university students' attitudes. Additionally, these two variables accounted for 67.5% of the variance in the university students' perceived behavioral control and 59.3% of the variance in their behavioral intention to use GAI technology.

4.6. SEM Stability test

Examining model stability is crucial for verifying SEM adaptability. An excellent model should possess high

Table 5. Model fitting indicators.

Fit indices	Model indicator values	Standard	Conclusion	Source
CMID	695.373	The smaller, the better	This part of the data is affected by the sample size, so there is no specific execution standard	
DF	337	The smaller, the better		
CMID/DF	2.063	<5 Acceptable; < 3 Good fit	Good fit	Hayduk (1987)
GFI	0.828	>0.8 Acceptable; > 0.9 Good fit	Acceptable	Bagozzi and Yi (1988)
CFI	0.930	>0.8 Acceptable; > 0.9 Good fit	Good fit	Bagozzi and Yi (1988)
TLI (NNFI)	0.921	>0.8 Acceptable; > 0.9 Good fit	Good fit	Hair et al. (2017)
RMSEA	0.066	<0.08	Good fit	Hair et al. (2017)
SRMR	0.061	<0.08	Good fit	Hu and Bentler (1998)

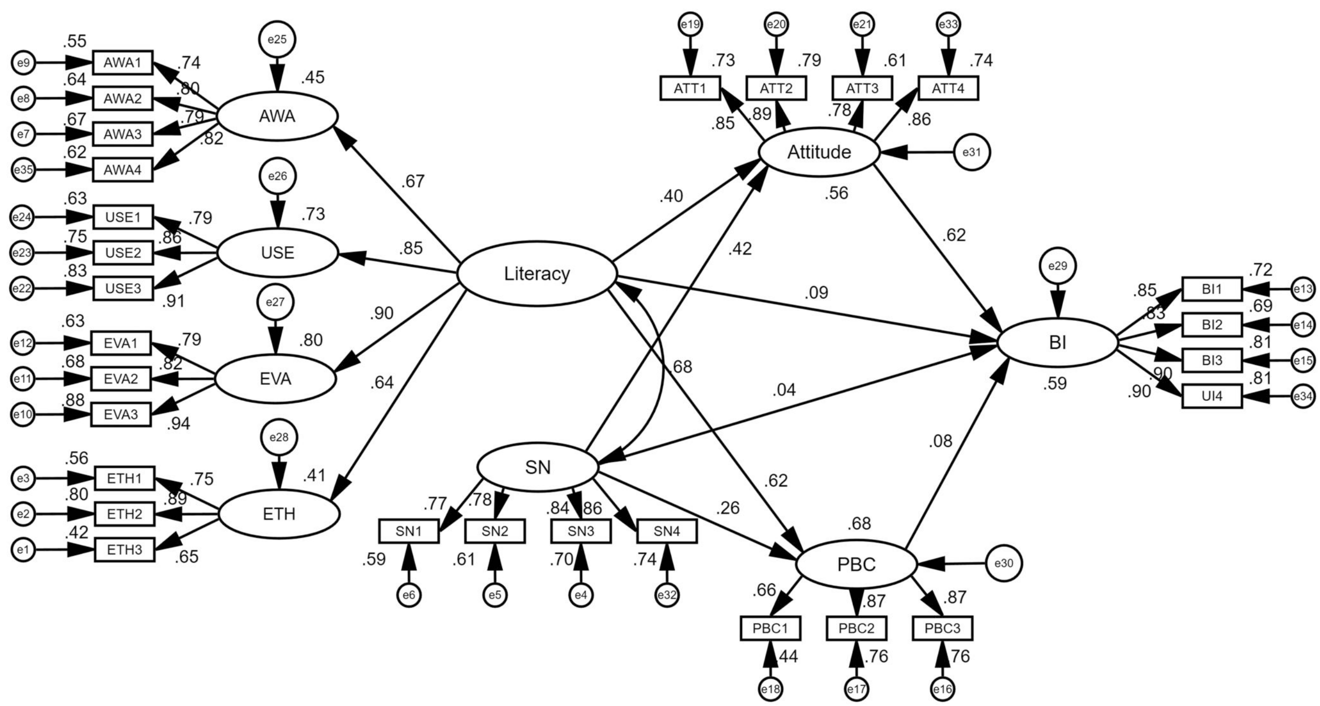

Figure 3. Structural model diagram.

Table 6. Weight distribution in second-order models.

Second-order variable	First-order variable	P	Impact weight
AI literacy	AWA→AI literacy	***	0.668
	USE→AI literacy	***	0.855
	EVA→AI literacy	***	0.895
	ETH→AI literacy	***	0.637

Table 7. Structural model path analysis results.

Hypothesis	Relationship	UnStd.	S.E.	C.R.	P	Std.(β)	R^2
H1	AI literacy → ATT	0.436	0.097	4.498	***	0.398	0.557
H4	SN → ATT	0.322	0.063	5.096	***	0.416	
H3	AI literacy → PBC	0.824	0.130	6.342	***	0.623	0.675
H6	SN → PBC	0.243	0.072	3.376	***	0.260	
H2	AI literacy → BI	0.097	0.128	0.754	0.451	0.086	0.593
H5	SN → BI	0.031	0.068	0.461	0.645	0.039	
H7	ATT → BI	0.644	0.090	7.184	***	0.624	
H8	PBC → BI	0.070	0.089	0.786	0.432	0.082	

Note: ***$p < 0.001$.

explanatory power across different control variables among the study population. Therefore, this study introduced three control variables (sex, grade level, and major) to test the robustness of the hypothesized model. The results are shown in Figure 4.

The primary purpose of including control variables in SEM is to account for the influence of other variables on the relationships between the dependent and independent variables, thereby providing a more accurate assessment of the relationships (Liu et al., 2021). Despite the introduction of control variables, the influential relationships and significance levels among the latent variables in the model remained unchanged compared to when no control variables were included. Further, the overall model fit indices did not change significantly, and the impact of each control variable on behavioral intention to use GAI technology was not significant. This indicated that the model possessed high stability and did not undergo significant changes owing to variations in the control variables among the study population, thus demonstrating high generalizability.

4.7. Mediation analysis

Examining the underlying mechanisms through a mediation analysis is a crucial aspect of SEM. Therefore, this study employed the bootstrapping method with confidence intervals (CI) to conduct a mediation analysis; this is widely recognized as the most advantageous approach in current mediation testing (MacKinnon et al., 2002). Additionally, Hayes (2009)

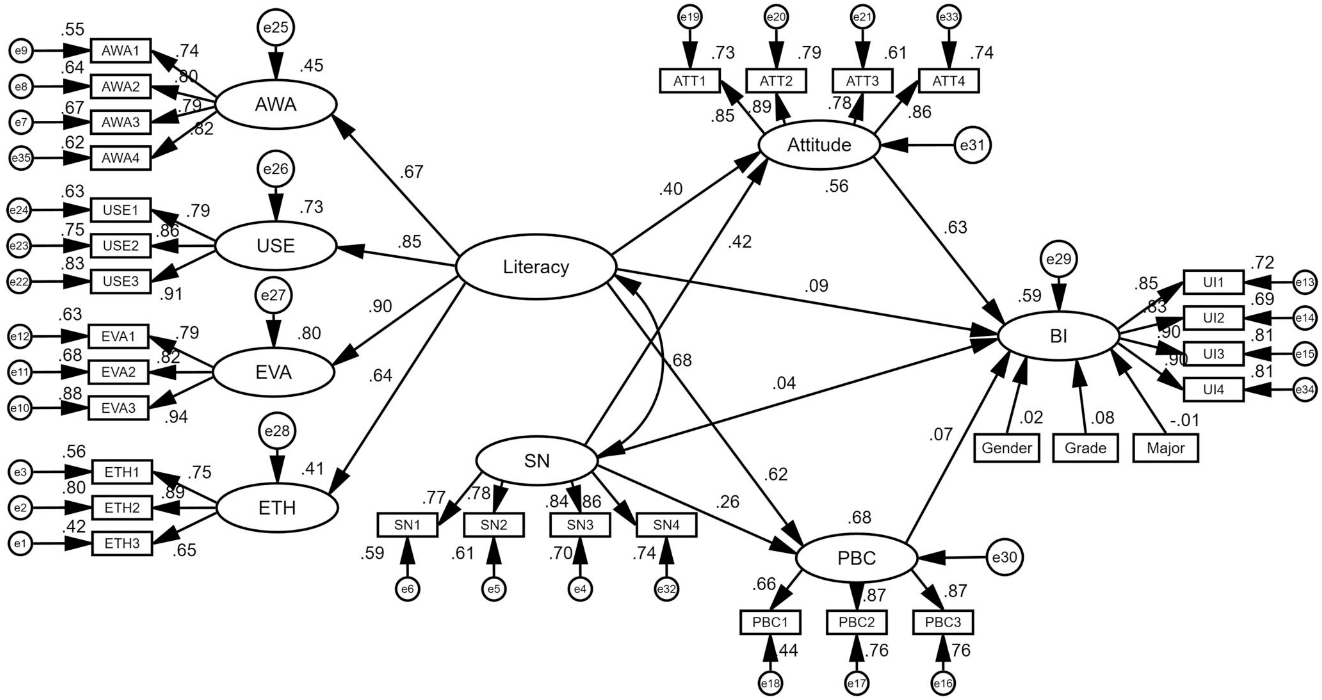

Figure 4. Stability Test diagram of structural model.

Table 8. Mediation analysis results of "AI literacy→ ATT→ BI."

			Coefficient multiplication		Bootstrapping				
					Bias-corrected 95% CI		Percentile 95% CI		
Path	Effect Type	Point Estimate	SE	Z	Lower	Upper	Lower	Upper	Mediation Type
AI literacy→ ATT→ BI	Total Effect	0.703	0.144	4.882	0.447	1.001	0.464	1.036	Full Mediation
	Indirect Effect	0.529	0.134	3.948	0.309	0.820	0.316	0.831	
	Direct Effect	0.174	0.141	1.234	−0.063	0.494	−0.068	0.481	

Table 9. Mediation analysis results of "SN → ATT→ BI."

			Coefficient multiplication		Bootstrapping				
					Bias-corrected 95% CI		Percentile 95% CI		
Path	Effect Type	Point Estimate	SE	Z	Lower	Upper	Lower	Upper	Mediation Type
SN → ATT→ BI	Total Effect	0.466	0.065	7.169	0.340	0.598	0.338	0.596	Full Mediation
	Indirect Effect	0.373	0.085	4.388	0.219	0.550	0.213	0.545	
	Direct Effect	0.093	0.088	1.057	−0.061	0.289	−0.068	0.278	

recommends bootstrapping as a favorable choice for calculating the indirect effects, provides specific operational procedures and relevant parameter criteria, and considers a minimum of 1,000 bootstrap samples with 5,000 samples as optimal. Following Hayes' (2009) recommendation, this study adhered to the suggested sampling frequency.

This study identified two instances of mediating effects. First, the study examined whether there was a mediating effect in the path from "AI literacy" to "Behavioral intention to use AI" with "Attitude" serving as the mediator. The results (Table 8) revealed that the direct effect was not statistically significant (bias-corrected 95% CI and percentile 95% CI including 0, $Z = 1.234 < 1.96$), whereas both the total and indirect effects were statistically significant (bias-corrected 95% CI and percentile 95% CI not including 0, Z values exceed 1.96). These results suggested the presence of a mediating effect on this path, indicating a complete mediating effect.

This study then conducted a mediation analysis with bootstrapping on the "Subjective norms–Behavioral intention to use AI" path. The results (Table 9) demonstrated that the direct effect was not statistically significant (with bias-corrected 95% CI and percentile 95% CI including 0, $Z = 1.057 < 1.96$), whereas both the total and indirect effects were statistically significant (with bias-corrected 95% CI and percentile 95% CI not including 0, Z values exceeding 1.96). These results indicated the presence of a mediating effect in this path, specifically characterized as a complete mediation effect. The remaining potential paths in the model's mediation analysis did not meet the requirements for establishing mediating effects. Therefore, it was not possible to conduct mediation tests on these paths.

5. Discussion

5.1. The role of attitude

The SEM results revealed that subjective norms and AI literacy significantly influenced university students' attitudes toward GAI technology. This finding is consistent with that of Ho et al. (2017), who demonstrated the significance of subjective norms on users' decisions regarding the adoption of Cloud technology, as well as Su and Yang (2024), who observed that children's AI literacy affected their perceptions of and attitudes toward robots in engineering and science. This may be because subjective norms encompass the influence of societal pressures and moral principles on individuals' behavior, thereby facilitating the adoption and endorsement of specific behaviors (Zhuang et al., 2021). AI literacy also reflects individuals' proficiency and expertise in AI-related knowledge and skills, thereby influencing university students' comprehension and acceptance of AI (Kang et al., 2023).

The interview findings provided additional support for the aforementioned pathways. Participant I7 stated that:

> I possessed an in-depth comprehension of AI principles, enabling my proficient utilization of AI to address various life and educational challenges. GAI technology served as a formidable productivity tool, thereby fostering my receptive and positive stance toward it.

This exemplified the impact of AI literacy on university students' attitudes toward GAI technology. The participants also shared noteworthy insights concerning subjective norms. Notably, Participant I11 stated that:

> My peers extensively use ChatGPT to troubleshoot code and tackle diverse predicaments. Their endorsement of such cutting-edge AI tools influenced my initial perception of ChatGPT and similar AI tools.

This finding underscores the significance of technology adoption and application, which frequently rely on endorsements from peers and educators. This resonates with the findings of Wang et al. (2023), who emphasize that the level of AI literacy shapes university students' attitudes toward AI. The greater the university students' comprehension of AI, the greater their awareness of AI's characteristics. This subsequently facilitates the recognition and acceptance of AI's current status as an auxiliary tool that can address intricate challenges in the learning process (Kong et al., 2021).

The notable influence of subjective norms and AI literacy on university students' attitudes toward GAI technology underscores the need for educational leaders to purposefully foster students' AI literacy. Educators can achieve this through pedagogical activities (Ng et al., 2022) and curricula (Dai, 2024) that guide students in cultivating values and ethical perspectives, thereby enhancing their understanding and awareness of AI. This approach can also facilitate students' comprehension of AI's practical applications and evolutionary progress, enabling them to accurately and objectively assess GAI technology. It can further encourage them to adopt positive attitudes toward AI, which, in turn, can foster their behavioral intention to utilize GAI technology in the learning process.

AI's rapid progress has necessitated its integration into educational systems worldwide, and its widespread adoption and advancement has become imperative in contemporary education. This study's findings emphasized the significance of prioritizing the development of students' subjective norms and AI literacy when applying AI in educational contexts, so as to enhance university students' attitudes and perspectives toward AI. Accordingly, the AIED field should build strong connections within society and industry and emphasize the fostering of students' practical and innovative capabilities. This integration is crucial for advancing the implementation of AIED (Chen et al., 2024). This study's results provide valuable insights for understanding the pertinence and effectiveness of AIED, thereby facilitating its wider adoption and progression. The future research and practice should delve deeper into investigating the efficacy and methodologies of AIED in response to the increasing demand for AI professionals driven by socioeconomic development.

5.2. The role of perceived behavioral control

Perceived behavioral control encompasses individuals' perceptual and cognitive assessments of their environment and personal capabilities, as well as their anticipated evaluations of potential outcomes. These factors subsequently influenced individuals' ability to regulate their own behavior (Holland & Piper, 2016). In the AIED field, perceived behavioral control is important for shaping individuals' utilization and application of AI (Adelana et al., 2024). This study's findings revealed that subjective norms and AI literacy had a substantial impact on university students' perceived behavioral control. This finding appears inconsistent with that of Hagger et al. (2022), who assert that perceived behavioral control does not moderate subjective norm intention. Hagger et al.'s (2022) study is grounded in the health behavior context wherein perceived behavioral control may be more stringent than in the educational context, given the substantial implications for health and life in the medical field, thus necessitating the need for more rigorous and precise behavioral control measures. While many studies have treated subjective norms, AI literacy, and perceived behavioral control as independent moderators to explore their effects on attitudes toward technology, to date, few studies have analyzed the influence of subjective norms and AI literacy on perceived behavioral control. Therefore, to gain a deeper understanding of the underlying mechanisms governing the relationships between these variables, conducting comprehensive analyses informed by the AI literacy research (Wang et al., 2023) and the TPB yields valuable insights.

Prior to engaging in action, individuals consider social expectations and prevailing attitudes, which play pivotal roles in shaping their evaluation and decision-making processes (Vicente & Partidário, 2006). In the AIED field, if university students perceive the utilization of GAI technology as being advantageous and valuable, they will demonstrate a stronger inclination to embrace it, which, in turn, will augment their perceived behavioral control. Conversely, when university students perceive GAI technology to have negative repercussions or lack social acceptance, their behavioral intention to adopt GAI technology will diminish, consequently affecting their perceived behavioral control. For example, Participant I1 stated:

> It is very common to use ChatGPT in daily studies and practice. I am a Computer Science and Technology major, so we should embrace technological advancements. Our course instructors encourage us to use ChatGPT technology and have demonstrated it in class as an efficient and innovative productivity tool that can enhance our learning and work efficiency.

Thus, AI literacy influenced perceived behavioral control. This perspective was substantiated through the interview results, as exemplified by Participant I3, who remarked that:

> When numerous classmates informed me that using ChatGPT was uncomplicated and that it facilitated the resolution of diverse real-life and educational challenges, I realized that there were no barriers to utilizing AI products.

Although the TPB does not explicitly incorporate the AI literacy variable, it recognizes the significance of competence and knowledge as influential factors in behavior. Consequently, within the AIED field, the TPB inherently acknowledges the importance of university students' proficiency in GAI technology as it relates to the effectiveness and controllability of their actions and behaviors. Individuals with a higher level of mastery and understanding of GAI technology exhibit greater confidence and control over their actions (Chai et al., 2021). Conversely, limited or nonexistent familiarity with GAI technology reduces individuals' behavioral usage intention, which, in turn, affects their perceived behavioral control. The interviews provided evidence supporting this perspective, as exemplified by Participant I11, who stated that:

> Upon completion of the foundational course in AI, I acquired essential knowledge of AI principles. I discovered that AI was not inherently challenging. With a fundamental understanding of its principles, I became more adept in using AI-integrated products and software. Examples include photo-taking applications featuring automatic face recognition and image editing software that leverages GAI technology.

A deeper analysis of the underlying mechanisms associated with these two pathways revealed that individuals' attitudes and expectations regarding GAI technology were influenced by their AI literacy level. This interaction created a positive feedback loop, wherein individuals who possessed a higher level of AI literacy demonstrated more favorable attitudes and expectations toward AI, consequently strengthening their perceived behavioral control. For example, Participant I9 stated that:

> Being proficient in using various GAI tools can improve the efficiency of completing academic and other work tasks. For instance, drawing tasks can be done using GAI products like Midjourney or DALL-E 3. Some text-related tasks can be handled by ChatGPT-4, which can now also process simple documents and generate code to complete some uncomplicated tasks, including basic data processing and data visualization. Therefore, I am looking forward to the further advancements in this technology and will continue to monitor its development and continuously learn about and use it.

Moreover, a potential reciprocal relationship existed between individuals' subjective norms and AI literacy. Students' attitudes and expectations toward GAI technology can be shaped by social and cultural factors, thereby forming subjective norms (Ursavaş et al., 2019). Simultaneously, individuals' competence in GAI technology can be influenced by social and cultural factors, leading to the development of AI literacy that encompasses cultural and social awareness, specifically the ethical cognition aspect of AI literacy. These social and cultural factors may affect individuals' subjective norms and AI literacy, consequently influencing their perceived behavioral control. This finding resonates with that of Chai et al. (2022), who suggest that learning about AI while considering its social impacts facilitates university students' continuous development of AI competency.

In sum, the influence of individuals' subjective norms and AI literacy on perceived behavioral control is significant and shaped by social and cultural factors. Hence, in the dissemination and implementation of GAI technology, there is a critical need to strengthen individuals' AI literacy, augment their comprehension and mastery of AI, and concurrently leverage their social and cultural influences to cultivate positive attitudes and expectations toward GAI technology. Doing so can elevate individuals' levels of perceived behavioral control, enabling them to proficiently employ and apply GAI technology in the educational context.

5.3. The role of Behavioral intention to use AI

The SEM results revealed a direct association between individuals' attitudes toward AI and usage intention. University students' positive attitudes were positively correlated with a stronger inclination to utilize GAI technology, thereby increasing behavioral usage intention. Conversely, university students' negative attitudes might lead to resistance toward adopting AI, thereby reducing their behavioral usage intention. These findings are consistent with those of Lam et al. (2007), Chang et al. (2017), and Revythi and Tselios (2019), who suggest a relationship between behavioral intention and attitudes toward using technology. Numerous studies have demonstrated that GAI technology can assist learners in many learning tasks, leading to improved learning performance and satisfaction, which, in turn, results in learners being more willing to use GAI technology in the present and future. For example, Yilmaz and Yilmaz (2023a) confirmed that ChatGPT could enhance students' computational thinking skills, programming self-efficacy, and motivation. Moreover, Jing et al. (2024) assert that learners with positive attitudes toward GAI technology are more willing to use GAI products, such as ChatGPT, highlighting the close relationship between attitude and intention.

This study's interview insights elucidated the complexity of attitude, including the cognitive and experiential dimensions. Individuals who believed that GAI technology could provide better experiences and outcomes demonstrated greater intention to overcome challenges and barriers, thereby promoting the adoption and utilization of GAI technology. This result is consistent with that of Liesa-Orús et al. (2023), who indicate that university students' attitudes directly and significantly influence their positive behavioral intention toward technology.

During the interviews, many participants highlighted the impact of affective attitudes toward GAI technology on their propensity to adopt it. Notably, Participant I5 stated that:

> Given the appropriate regulation, GAI technology possesses the potential to substantially enhance diverse facets of human existence. I am optimistic about the future progression of GAI technology and actively engaging with the cutting-edge advancements, including ChatGPT, while diligently exploring its practical implementations.

While AI literacy and subjective norms did not directly influence the university students' behavioral intention to use GAI technology, they significantly impacted their attitude toward it. Therefore, attitude served as an indirect pathway that affected behavioral intention to use GAI technology. Thus, it is essential to recognize the importance of AI literacy and subjective norms when shaping the intention to adopt GAI technology. This finding aligns with that of Ma and Lei (2024), who assert that as new AI teaching tools are introduced into schools, and societal perceptions of GAI technology continue to evolve, university students' intention to use GAI may undergo adjustments, presenting both challenges and new opportunities. This finding is also consistent with that of Yilmaz and Yilmaz's (2023a) quasi-experimental study. This study then conducted a mediation analysis to explore the mediating effects. The results demonstrated that AI literacy and subjective norms indirectly influenced university students' behavioral intention to use GAI technology through attitude, which served as a mediator. This finding underscores the importance of university students' attitudes toward GAI technology and indirectly emphasizes the significance of AI literacy and subjective norms as essential independent variables that require careful consideration.

Many studies have validated the importance of literacy (Çelebi et al., 2023; Wang et al., 2023; Yilmaz & Yilmaz, 2023a, 2023b). When faced with a new technological product with immense potential, it is crucial to cultivate students' knowledge and critical thinking skills to address the ethical considerations and potential biases associated with AI-generated outputs. By providing students with these skills, educators can enable them to make informed decisions and responsibly use GAI tools, thereby promoting the more ethical and responsible use of AI technology in their academic and professional pursuits (Çelebi et al., 2023; Chen et al., 2024; Jing et al., 2024; Kong et al., 2021).

In sum, the relationship between attitude and behavioral intention to use GAI technology is characterized by a complex interplay and reciprocal influence. Attitude, a multifaceted construct, is influenced by university students' AI literacy and subjective norms. This aligns with the TPB, which posits that attitudes toward behavior, subjective norms, and perceived behavioral control shape individuals' behavioral intention. Consequently, a comprehensive approach based on this theoretical framework is essential for the promotion and application of GAI technology. This approach should entail enhancing individuals' objective comprehension of GAI technology and considering their social and cultural contexts. Understanding and leveraging AI literacy and subjective norms can provide deeper insights into the mechanisms driving behavioral usage intention. Respecting individuals' attitudes and choices are of paramount importance in effectively fostering their adoption and advancement of GAI technology in the educational domain. This theoretical integration underscores the importance of a holistic strategy that incorporates cognitive and social dimensions to promote the effective use of GAI technology.

6. Implications

6.1. Theoretical implications

The TPB is an important behavioral intention prediction framework within the social sciences and has garnered widespread recognition among academia (Chai et al., 2020; Habibi et al., 2023; Otache, 2019). This study enhances the TPB by incorporating AI literacy as a relevant variable in the research model. By applying this improved theoretical framework, this study effectively elucidates the factors that influence university students' behavioral intention to adopt GAI technology. This study's primary theoretical value lies in its ability to expand the specific contexts and boundaries of the TPB, thereby broadening its applicability and reaffirming its flexibility and adaptability.

The theoretical significance of this study also lies in its comprehensive investigation of the TPB, resulting in an enhanced comprehension of the theory alongside the provision of novel perspectives and approaches for forecasting and elucidating behavioral intention and patterns related to GAI technology utilization in the social sciences. This study also provides a reference for the exploration and implementation of AI literacy. Unlike general AI services, GAI systems such as ChatGPT and Sora possess unique characteristics, including the ability to generate human-like text and high-quality video content, which present distinct cognitive and ethical considerations. By focusing on GAI, this study addresses the unique challenges and opportunities associated with this technology and offers insights that are particularly novel and relevant to the educational domain. This study ultimately presents a theoretical framework and research methodology that can be adopted by the future studies, so as to foster the advancement and integration of GAI technology within the educational domain and elevate the level of educational modernization.

6.2. Practical implications

This study has several practical implications. First, the findings provide compelling empirical evidence that can guide university administrators, educational leaders, and teams engaged in designing and developing educational products. The findings can empower them to formulate effective strategies based on a thorough understanding of the factors that influence university students' behavioral intention to adopt GAI technology.

Second, this study offers valuable practical insights into universities' design of pertinent educational activities through a comprehensive investigation of the pivotal concept of AI literacy. The findings underscore the pressing need and essentiality of augmenting AI literacy among university students. As such, this study proposes a plethora of pragmatic strategies, such as the implementation of AI literacy courses and the provision of opportunities for hands-on engagement in GAI technology. The adoption of such strategies will advance the educational modernization process.

Third, this study reveals the unique applications and benefits of GAI technology compared with general AI services. GAI technology can produce personalized educational content and interactive learning experiences, which can significantly enhance student engagement and learning outcomes. Thus, GAI technology has specific benefits and implementation strategies that are unique and can provide a more targeted approach for educators and policymakers.

In sum, the practical ramifications of this study extend beyond the advancement of AI development within universities by providing practical knowledge and a reference for the application and dissemination of GAI technology. This study's focus on the distinctive attributes of GAI ensures that the strategies and recommendations offered are innovative and contextually relevant, so as to maximize their impact and efficacy in the education field.

7. Limitations and future research

Although this study provides valuable insights into the factors that influence university students' behavioral intention to accept GAI technology, it has certain limitations that require further refinement and improvement in the future research. First, this study was constrained by time and cost factors, resulting in a sample size that did not meet the recommended optimal standard. Although the sample size was within a reasonable range, it may have affected the generalizability of the results.

Second, this study had regional limitations, as the sample primarily consisted of university students from higher education institutions in Zhejiang Province. This may have led to similar educational experiences and high cultural homogeneity within the sample. Yilmaz and Yilmaz (2023b) and Çelebi et al. (2023) state that a lack of cultural differences can limit the generalizability of the results, thereby affecting the broad applicability of the conclusions in other cultural contexts. The future research should include samples from diverse cultural backgrounds and geographical areas to enhance the universality and applicability of this study's findings.

Third, this study employed a second-order model to investigate the association between behavioral intention and behavior. Although this approach simplified the parameter estimation, it may have somewhat compromised the overall model fit. Consequently, certain goodness-of-fit indices did not meet the predefined criteria for good fit. This indicates that there are still gaps and uncertainties in this study's comprehension of the relationship between behavioral intention and behavior. To address this issue, the future investigations should explore alternative and more sophisticated techniques, such as long-term observational tracking or laboratory experiments, to gain further insights into the connection between behavioral intention and behavior. Additionally, incorporating cross-validation using multiple methodologies may enhance the reliability and accuracy of the findings.

In sum, this study had certain limitations, particularly regarding the scope of the research sample and the influence of the second-order model on the overall model fit. To enhance the comprehension and prediction of human behavior, the future research should undertake a more comprehensive investigation of the intricate relationship between behavioral intention and behavior. Further, the future studies should employ cross-validation techniques involving multiple methodologies to bolster the reliability and precision of the findings. Doing so can contribute to the advancement of related studies and applications in the realm of social sciences, offering improved support and guidance for the academic community.

8. Conclusion

Based on the TPB, this study combined SEM and interview data to analyze the factors that influenced university students' behavioral intention to use GAI technology. The conclusions were as follows. Regarding **RQ1**, this study investigated the AI literacy of university students in Zhejiang Province and found that among the four specific literacies, AI ethical cognition literacy scored the highest ($M = 5.740$), whereas AI consciousness literacy scored the lowest ($M = 4.578$). This indicated that although the students had a high awareness of the ethical implications of AI, their overall awareness and understanding of AI concepts and applications were lacking. Therefore, improving AI consciousness literacy may be a key area for future educational interventions.

Regarding **RQ2**, the results found that university students' attitudes toward GAI significantly and positively influenced their behavioral intention to use GAI technology. This suggests that fostering a positive attitude toward GAI can increase its adoption among students. By combining AI literacy with the TPB, the results explained 59.3% of the variance in university students' behavioral intention to use GAI technology. This high explanatory power underscores the importance of AI literacy and the TPB framework in understanding students' behavioral intention.

Regarding **RQ3**, the results revealed that AI literacy and subjective norms significantly and positively influenced university students' attitudes toward GAI technology and their perceived behavioral control. This highlights the roles of social influence and self-efficacy in shaping students' attitudes and perceived capabilities. Therefore, educational programs should not only focus on enhancing AI literacy but should also consider students' social context and support systems to boost their confidence and attitudes.

Finally, regarding **RQ4**, the results found that attitude was an important mediating variable within the proposed model framework. Specifically, it fully mediated the effects of AI literacy and subjective norms on behavioral intention to use GAI. This finding emphasizes that interventions aimed at improving AI literacy and shaping positive subjective norms can indirectly enhance students' behavioral intention by influencing their attitudes.

Through the qualitative interviews, this study also deconstructed the relationships between the aforementioned variables and analyzed the university students' decision-making mechanism regarding their behavioral intention to use GAI. The interviews revealed nuanced insights into how the students perceived and interacted with GAI technology, which complemented the quantitative findings. For example, some students expressed concerns regarding data privacy and the ethical use of AI, which must be addressed to foster more positive attitudes and higher usage intention in the future.

Based on the analysis, this study provides relevant suggestions and strategies for university management and educational leadership. For example, universities should implement comprehensive AI literacy programs that cover the ethical, cognitive, and application aspects of AI. These programs should be designed to impart knowledge and positively influence students' attitudes and perceived behavioral control by leveraging their social influences and providing practical experiences with GAI technology. Considering the current development trends in GAI technology, this study emphasizes the importance of improving university students' AI literacy. Practical recommendations and insights are provided for universities facing the impacts of emerging GAI technology. For instance, integrating GAI into the curriculum and providing hands-on workshops can help students to develop a deeper understanding of and more positive attitudes toward this technology.

Given the significant impact of GAI technology on the current educational ecosystem, it is a crucial topic that must be considered and evaluated by all relevant stakeholders, such as university students, teachers, and educational leaders. This study offers useful recommendations for university students and teachers, as everyone in the education ecosystem should be prepared for the future influence of GAI. Thus, educational models and learning approaches should embrace and adapt to new technology. This will involve integrating GAI into educational practices and continuously evaluating and updating these practices to align with the evolving technological landscape.

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Data availability statement

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

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Appendix A

Table A1. The results of the reliability and convergent validity of the pretest.

Dimension	Items	Significance estimation				Std.	Operations on the items	Cronbach's alpha
		Unstd.	S.E.	z-value	*p*-value			
Awareness of AI	AWA1	1.000				0.539	Delete	0.883
	AWA2	1.299	0.231	5.633	***	0.842	Retain	
	AWA3	0.749	0.176	4.261	***	0.591	Delete	
	AWA4	1.170	0.222	5.280	***	0.770	Retain	
	AWA5	1.482	0.256	5.787	***	0.877	Retain	
	AWA6	1.298	0.247	5.249	***	0.764	Retain	
Usage of AI	USE1	1.000				0.857	Retain	0.905
	USE2	0.962	0.110	8.756	***	0.859	Retain	
	USE3	0.971	0.105	9.214	***	0.905	Retain	
Evaluation of AI	EVA1	1.000				0.923	Retain	0.831
	EVA2	0.761	0.133	5.712	***	0.719	Retain	
	EVA3	0.736	0.137	5.372	***	0.674	Retain	
Ethics of AI	ETH1	1.000				0.660	Retain	0.789
	ETH2	1.156	0.384	3.009	***	0.916	Retain	
	ETH3	0.883	0.244	3.616	***	0.667	Retain	
Subjective Norms	SN1	1.000				0.872	Retain	0.890
	SN2	0.870	0.114	7.660	***	0.788	Retain	
	SN3	1.077	0.139	7.745	***	0.794	Retain	
	SN4	0.921	0.109	8.414	***	0.841	Retain	
Perceived Behavioral Control	PBC1	1.000				0.815	Retain	0.845
	PBC2	1.227	0.178	6.910	***	0.921	Retain	
	PBC3	1.028	0.170	6.046	***	0.699	Retain	
Attitudes	ATT1	1.000				0.921	Retain	0.905
	ATT2	0.872	0.099	8.841	***	0.811	Retain	
	ATT3	0.968	0.104	9.343	***	0.836	Retain	
	ATT4	0.847	0.101	8.429	***	0.790	Retain	
Behavioral Intention to Use AI	BI1	1.000				0.867	Retain	0.913
	BI2	1.212	0.120	10.072	***	0.911	Retain	
	BI3	1.174	0.138	8.539	***	0.823	Retain	
	BI4	0.920	0.109	8.450	***	0.818	Retain	

Note: $^{***}p < 0.001$; Based on factor loadings (i.e., Std. in the table), items AWA1 and AWA3 were deleted. The remaining items under the AWA variable were renumbered as AWA1 to AWA4.

Table A2. Discriminant validity table of the pretest.

	CR	AVE	Discriminant validity							
			ETH	EVA	USE	AWA	PBC	BI	ATT	SN
ETH	0.797	0.573	**0.757**							
EVA	0.820	0.608	0.646	**0.780**						
USE	0.906	0.764	0.425	0.762	**0.874**					
AWA	0.877	0.549	0.291	0.732	0.595	**0.741**				
PBC	0.856	0.667	0.349	0.676	0.628	0.631	**0.817**			
BI	0.916	0.732	0.314	0.489	0.336	0.365	0.400	**0.856**		
ATT	0.906	0.707	0.522	0.632	0.465	0.402	0.493	0.660	**0.840**	
SN	0.894	0.680	0.521	0.608	0.421	0.633	0.568	0.496	0.714	**0.825**

Note: The bold numbers on the diagonal represent the root of AVE, and the lower triangle represents the Pearson correlation coefficient of the facet. To meet the standard for discriminant validity, the square root of the AVE must be greater than the Pearson correlation coefficients between variables. Therefore, the discriminant validity analysis of the pilot test indicates that the questionnaire has high discriminant validity.

Table A3. Questionnaire items.

Construct	Items	Source
The Awareness of AI	AWA1: I understand how GAI products like ChatGPT achieve human-machine interaction. AWA2: I can recognize the artificial intelligence technologies used in the applications (e.g., Douyin, Taobao) and products (e.g., robotic vacuum cleaners) that I use. AWA3: I understand why GAI technology rely on big data. AWA4: I understand how GAI technology optimizes the translation output of online translation. AWA5: I understand how GAI products process images to achieve visual recognition functionality. AWA6: I know how GAI products like ChatGPT and Gemini perform speech recognition tasks.	Wang et al. (2022); Chai et al. (2020)
The Usage of AI	USE1: I can proficiently use AI applications (e.g., ChatGPT or Sora) or products to assist me in my daily tasks. USE2: I usually find it easy to learn how to use new GAI applications or products. USE3: I can use GAI applications or products to enhance my work efficiency.	Wang et al. (2022)
The Evaluation of AI	EVA1. I can evaluate the functionality and limitations of GAI applications (e.g., ChatGPT or Midjourney) or products after using them for a period. EVA2: I can choose the appropriate solution from the various solutions provided by GAI-related applications and products. EVA3: I can select the most suitable GAI application or product for various specific tasks.	Wang et al. (2022)
The Ethics of AI	ETH1: When using GAI applications or products, I always adhere to ethical principles. ETH2: When using GAI applications or products, I am vigilant about privacy and information security issues. ETH3: I am always vigilant about the misuse of GAI technology.	Wang et al. (2022)
Subjective Norms	SN1: My parents support me in learning how to use GAI technology. SN2: Most people I know believe that I should learn how to use GAI technology. SN3: My classmates believe it is necessary to learn how to use GAI technology. SN4: My teachers believe it is necessary to learn how to use GAI technology.	Ajzen (1985)
Perceived Behavioral Control	PBC1: Learning GAI-related technologies is relatively easy for me. PBC2: Applying GAI technology to assist me in work and study is relatively easy for me. PBC3: Applying GAI technology to solve problems in daily life is relatively easy for me.	Fishbein and Ajzen (2010); Van Lange et al. (2011)
Attitudes	ATT1: I think it is very wise to apply GAI technology to solve problems in daily life. ATT2: I find using GAI technology enjoyable. ATT3: I find using GAI technology for calculations very interesting. ATT4: I greatly enjoy the convenience brought by applying artificial intelligence technology.	Chai et al. (2020)
Behavioral Intention to Use AI	BI1: I will continue to keep an eye on the progress of GAI-related technologies. BI2: I will regularly update the latest GAI-related applications. BI3: I plan to use GAI to help me learn and work now and in the future. BI4: I will continue to apply GAI technology to solve problems I encounter in my life.	Chai et al. (2021)
Gender	£Male £Female (multiple-choice question)	
Level of Study	£Freshman £Sophomore £Junior £Senior £Graduate students (multiple-choice question)	
University	____________________ (fill-the-answer question)	
Major	£Science £Engineering £Humanities £Social Sciences (multiple-choice question)	

Note: The items AWA 1 and AWA 3 were not used in the formal measurement because they did not meet the reliability and validity standards during the pre-test phase.

Table A4. The demographic and sociological profile information of the interviewees.

No.	Major	Gender	Grade
I1	Computer Science and Technology	Male	Sophomore
I2	Software Engineering	Male	Sophomore
I3	Information Automation	Male	Sophomore
I4	Educational Technology	Female	Graduate student
I5	Information Automation	Male	Sophomore
I6	English	Female	Junior
I7	Chinese Language and Literature	Female	Junior
I8	Public Administration	Female	Senior
I9	Software Engineering	Male	Junior
I10	Educational Technology	Male	Sophomore
I11	Urban and Rural Planning	Female	Graduate student
I12	Psychology	Female	Senior
I13	Public Administration	Female	Freshman
I14	Law	Female	Sophomore
I15	Law	Female	Graduate student

Table A5. Open coding results of interview transcripts.

Category	Initial Concept (Provided partial representative interview segments)	Frequency
Improve performance	The GAI technology makes learning more efficient and enhances learning efficiency; it provides study materials and method suggestions; diversifies work; offers inspiration, enhances creative design inspiration, and expands creativity; improves skills; opens up new ways of learning, enabling independent exploration of knowledge; provides new knowledge and skills, helping to master knowledge.	34
Provide resources	The GAI technology can recommend a wealth of resources; suggest learning paths when I am learning new knowledge; offer new ideas and learning resources; provide various perspectives and modes of expression.	23
Enhance learning value	I'm not very proficient in programming, but in the field of design, I often need to use some less complex code. With the assistance of GAI technology, I feel more confident about my upcoming professional studies. Using GAI technology allows me to complete my designs more quickly, which gives me a great sense of achievement.	12
Optimize the learning experience	Make learning fun; make learning more enjoyable; make my learning more relaxed and less anxious; personalized and effective learning experience; real-time guidance and feedback; instant feedback; prompt responses.	14
Recommendation from the teacher	The teacher recommended us to use GAI technology to improve the efficiency of large-scale project design and development. The teacher also suggested that we try out some new technologies to master more advanced productivity tools.	9
Peer influence	Fellow students have given high praise for the GAI technology after using it. They recommend me to use GAI technology to address some repetitive tasks.	8
Media guidance	Some social media platforms, such as Bilibili and YouTube, often feature reports on GAI technology. Some media outlets heavily promote GAI technology.	7
Technical awareness	GAI technology boasts powerful productivity features; it is innovative, accurate, and practical; GAI technology provides extremely timely responses; it offers prompt suggestions and guidance.	11
User experience	Using ChatGPT to complete large projects allows me to focus more on the top-level design of the project, rather than getting bogged down in minor details; it saves time; it is convenient and efficient; highly effective; easy to apply; provides convenience.	23
subjective attitude	Translate to English: "GAI technology is very good and helps me solve many problems; I find GAI technology too efficient in handling paperwork."	7
Self-competency assessment	Having a certain foundation in information technology, one can use this tool proficiently; believing in one's ability to master GAI technology; GAI technology does not require high technical demands, and many people can use it; however, using GAI technology effectively still requires a certain level of understanding of it.	34
Rational cognition	Fully functional; advantages lie in text generation capabilities; powerful natural language processing abilities; excellent intelligent generation capabilities; professionalism and capability of GAI technology; intelligence and automation of GAI technology.	14
Moral identity	Using GAI technology is very normal, especially for me as a computer science professional; we should embrace technological advancements. The tool simply assists me in practice, I still need to design; I don't think using GAI technology is unethical.	27
Ethical judgment	Cheating using GAI technology is unethical behavior; in most cases, GAI technology is used to complete everyday tasks.	4
Subjective perception	Very clear about the tasks that GAI technology can help me complete; fully aware of the purpose of using this tool; the generative capabilities of GAI technology can inspire my work.	14
Behavioral identity	Strongly endorse the use of GAI technology to aid learning; fully support the use of GAI technology.	4
Behavioral intention orientation	In the future, I look forward to the personality of GAI technology; I intend to continue using GAI technology in the future; GAI technology has been very helpful for learning, so I will continue using it.	15

Note: The frequency represents the total count of relevant discussion segments appearing in the interview transcripts of 15 respondents. Repeated mentions by the same respondent are counted multiple times.