scientific reports

OPEN

Modeling teacher education students' adoption of large language models through an extended technology acceptance framework

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With the deepening integration of artificial intelligence (AI) technologies in the education sector, large language models (LLMs) have become essential tools for supporting writing tasks. As the future backbone of the teaching profession, the acceptance of these technologies by teacher education students not only influences their professional development but also plays a critical role in the digital transformation of future educational practices. However, existing research has yet to fully uncover the underlying mechanisms and influencing factors driving technology adoption behaviors within this group. This study extends the Technology Acceptance Model (TAM) by incorporating key variables such as learning motivation, perceived risks, self-efficacy, and usage experience. Using structural equation modeling (SEM), we analyzed survey data from 552 fourth-year teacher education students in China to test the proposed hypotheses. The empirical findings reveal that subjective norms are the strongest predictor of behavioral intention, while perceived ease of use significantly and positively influences attitudes toward using LLMs. Among the risk dimensions, perceived time risk exerts a significant negative effect on perceived usefulness, whereas perceived privacy risk negatively impacts perceived ease of use. Additionally, usage experience fosters technology adoption behaviors by enhancing learning motivation. These findings not only extend the application boundaries of the TAM within the field of educational technology but also provide empirical evidence for educational institutions to design technology training programs and for model developers to optimize user experiences. Furthermore, they offer a theoretical framework for building digital literacy training systems for teacher education students.

Keywords Teacher education students, Technology acceptance model (TAM), Large language model (LLM), Higher education, Structural equation model (SEM)

In recent years, artificial intelligence (AI) has been deeply integrated into various industries at an unprecedented pace, with the education sector increasingly recognizing its potential value in empowering teaching and driving reform[1]. As a novel advancement in AI, Large Language Models (LLMs) offer personalized learning resources[2], enhancing both the learning experience and outcomes[3]. Given their immense potential in educational support, teaching assistance, and research facilitation[4], LLMs have emerged as a significant catalyst for educational innovation[5].

A large body of research has been conducted in the field of higher education to examine the willingness to use LLMs in higher education cohorts[6]. Specifically, studies on student populations show that management and accounting students use LLMs for research tasks such as writing reports, task urgency (e.g., stress and anxiety) and the perceived helpfulness of the tool[7,8] influence their usage behavior. In contrast, for students in STEM disciplines, more attention is given to the technological interactivity of LLMs (e.g., interface usability, content adaptability). Their acceptance of LLMs is influenced by cognitive factors, including intrinsic motivation toward AI and self-confidence[9]. LLMs are more frequently used by students with higher anxiety levels to alleviate stress,

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but their adoption is constrained by the risks associated with the reliability of content generated through LLMs[10]. Meanwhile, students with lower self-efficacy require user interface design features (e.g., intuitive interfaces) to lower the barriers to use[11].

Research focusing on faculty members primarily addresses technological integration capabilities and adoption motivations. Teachers with higher Technological Pedagogical Content Knowledge (TPACK) are more likely to integrate LLMs into their classrooms, with their adoption being positively influenced by management support and available resources[12]. Regarding adoption motivations, teachers with high self-efficacy are more inclined to explore LLMs proactively, with their sustained use being driven by subjective norms (e.g., school policies) and attitudes. In contrast, teachers with high technological anxiety require training to increase tool familiarity and mitigate concerns about the risks of substitution[13]. However, there is limited research addressing the use of technology by teacher education students, particularly in developing countries, where the issue remains underexplored[14,15].

Teacher education students, as the future workforce of educators, represent a cornerstone of national educational development. At the same time, they occupy dual roles as both learners and educators[16]. Their degree of technology adoption plays a critical role in determining the breadth (whether educational technologies can be recognized and promoted across broader educational domains) and depth (whether teacher education students can, after thorough understanding, help their students more effectively grasp the use of these technologies) of educational technology integration. Consequently, understanding the factors that drive teacher education students' adoption of technology is of paramount importance. The primary objective of this study is to extend our understanding of fourth-year teacher education students' willingness to use LLMs for writing, through the lens of the TAM.

Since its introduction by Davis[17], the TAM has been widely applied to explore students' levels of technology adoption[18]. However, the traditional TAM framework exhibits two key limitations when analyzing the technology adoption behaviors of teacher education students using LLMs: first, the core variables of the model fail to capture the professional orientation of teacher education students; second, the model does not account for the risk dimensions specific to LLMs[19]. In light of these considerations, the objective of this study is to expand the scope of TAM, delving deeper into the factors influencing fourth-year teacher education students' willingness to use LLMs for writing. To achieve this, the study builds on the three-tiered structure of TAM—comprising "external variables, attitude, and intention"[17]—and integrates four external variables: learning motivation, self-efficacy, usage experience, and perceived risk, thereby extending the TAM framework to better suit the context of Chinese teacher education students.

Based on this, two research questions are proposed:

1. What is the acceptance intention of fourth-year teacher education students toward using LLMs for writing?
2. What factors may influence the acceptance intention of fourth-year teacher education students toward using LLMs for writing?

Aligned with the research objectives and questions, the paper is organized as follows: The second part reviews progress on LLM-assisted writing in higher education and TAM-related studies. The third formulates hypotheses within the theoretical framework. The fourth outlines the research methodology. The fifth presents the findings, while the sixth discusses their implications and limitations. Finally, the seventh concludes with insights for subsequent studies.

Literature review

Large language models

Large Language Models (LLMs), a crucial branch of artificial intelligence, refer to deep learning models constructed using complex neural network architectures and pre-trained on vast amounts of data[20]. These models, characterized by their massive parameter scales and sophisticated algorithmic design, not only exhibit emergent capabilities in language comprehension and generation but also possess generalized intelligence capable of addressing multimodal tasks[21].

The first technological breakthrough in language models occurred between the 1950s and 1980s when rule-based approaches were introduced, such as Chomsky's context-free grammar and the human–computer dialogue system ELIZA. Nevertheless, these methods were limited in their ability to scale and handle linguistic complexity. The second technological revolution came with statistical language models in the 1990s. With N-gram models and Hidden Markov Models (HMM), it was possible to predict word sequence probability through Google's billion-word corpus but they were still not capturing enough semantically. In the age of the twenty-first century, neural networks and the Transformer architecture initiated the third major technological revolution[22]. BERT[23] and the GPT series[24] played a great role in introducing self-attention methods and large-scale parameters training, that have become the cornerstone of LLMs such as ChatGPT, pushing language understanding, generation of text and multi-fold generalization to a new level.

At this stage of technological breakthroughs, an entire product ecosystem based on LLM technology has emerged. ChatGPT is the first LLM from OpenAI to enable a transformative interactive experience, and many follow-up applications, such as Anthropic's "CLAUDE" and Baidu's "Qwen", enable the deployment of large models across various scenarios. These LLMs are pre-trained using the latest technological paradigms, which excel in language comprehension and solving complex reasoning tasks. Moreover, these models have overcome traditional NLP limitations, not only performing fundamental tasks such as grammar correction and text generation but also demonstrating human-like reasoning abilities, including autonomously generating specialized text[25]. As a result, they have garnered significant attention from both academia and industry.

Currently, the application of LLMs in education is primarily explored in two major directions: first, examining the practical application of LLMs in education, including feasible integration pathways and the associated challenges; second, empirically validating the effectiveness, causal relationships, or potential risks of LLMs within educational contexts.

The first category of research focuses on the analysis of current practices, pathway design, or strategy development. Baig and Yadegaridehkordi[26] conducted a systematic review of 57 studies and found that scholars primarily use LLMs such as ChatGPT for assignments, assessments, exam design, student guidance, curriculum planning, and teaching, as well as course and syllabus design. Students primarily employ LLMs for language learning, communication skills training, online education, coding or programming, writing and translation, personalized learning, debugging, and fostering collaboration. Yan et al.[27] constructed a classification map of LLM applications in education through a meta-analysis of 118 studies. The research identified nine major application scenarios, from user profiling to content recommendation, with teaching support (31%) and content generation (22%) being the dominant areas.

Notably, insufficient technological maturity (mentioned in 68% of the studies) and a lack of ethical risk management (cited in 57% of the studies) were identified as key bottlenecks hindering further development. Zeb et al.[28] analyzed the opportunities (e.g., collaboration, personalized assessments) and challenges (e.g., academic integrity risks) associated with ChatGPT in higher education, emphasizing the need for policy formulation and training to ensure its responsible use.

The second category of research is based on empirical analyses of multidimensional influences, revealing the dual-edged impact of LLMs in the educational sector. On the positive side, numerous studies have confirmed that LLMs can significantly enhance students' overall writing abilities. Gayed et al.[29] innovatively developed the AI KAKU English writing assistance system using the GPT-2 architecture, finding that students in the experimental group demonstrated significant improvements in sentence fluency, semantic depth, and linguistic accuracy. In the realm of creative writing, Lee et al.[30] conducted an in-depth study using the GPT-3-powered Co Author online writing platform. This experiment involved 63 participants collaborating with four GPT-3 models, resulting in the generation of 1,445 text samples. Learners generally acknowledged improvements in writing skills across linguistic, conceptual, and collaborative dimensions. Further research revealed that this human-AI collaborative model increased writing efficiency by 37.2%.

On the negative side, related studies have exposed potential risks associated with LLMs in education. Ma et al.[31] conducted a quality assessment of scientific texts generated by ChatGPT, discovering that 15.8% of the content contained factual errors, with a misuse rate of specialized terminology reaching 22.4%. More alarmingly, an experiment by Levin et al.[32] showed that only 46.3% of academic abstracts generated by ChatGPT could be accurately identified by professional reviewers, a level of opacity that could exacerbate the risk of academic misconduct.

There is existing research that has shown that LLMs have a dual nature concerning education[33]. Nevertheless, little is known about systematic studies on LLMs among teacher education students in writing scenarios. Understanding the acceptance of such technologies by teacher education students is not only important for investigating the digital literacy of future educators but also for understanding the functional development and defining the ethical boundaries of LLMs in educational settings. Lee and Zhai[34] surveyed teacher education students who expect ChatGPT to provide precise questioning strategies, personalized learning, and formative assessment plans. At the same time, they express concerns about its content accuracy and remain cautious of the potential risks associated with technological dependency.

In light of the ongoing digital transformation in education, LLMs are poised to become deeply integrated into future teaching practices. Educators must urgently assess the new paradigm of human-AI collaboration with careful consideration[35]. A critical issue in teacher education students is: how can future educators acquire core competencies while cultivating a critical awareness of technology use?[36]. The TAM provides a significant research pathway in this context. Exploring the key variables that influence teacher education students' willingness to use LLMs not only offers valuable insights for developing digital literacy among future educators but also provides feedback for LLM developers to refine and optimize features tailored to educational needs.

Technology acceptance model

This theory is built on the Theory of Reasoned Action; Davis[17] developed TAM (Fig. 1) to explain individuals' information technology usage behaviors. There are four core variables in the TAM: perceived usefulness (PU), perceived ease of use (PEOU), attitude toward use (ATU), and behavioral intention (BI). Many studies have been conducted under the framework of TAM regarding the key drivers of users' acceptance of digital information

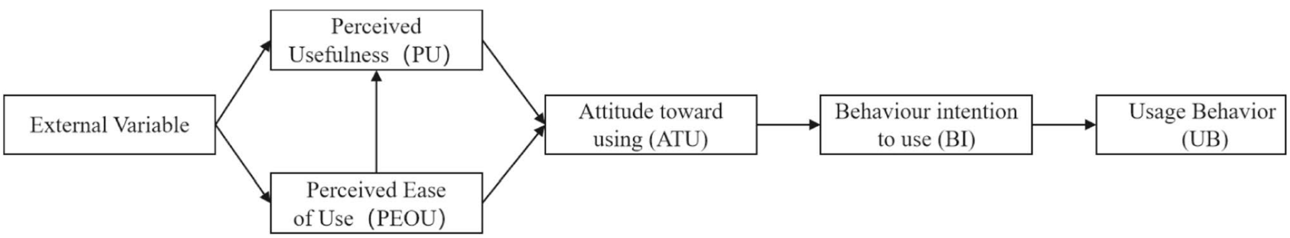

Fig. 1. Technology Acceptance Model (TAM). Source: Davis (1989).

technologies in the educational domain[37]. These emerging technologies include e-learning[38], online learning[39], metaverse technologies[40], and LLMs such as ChatGPT[41].

Among the studies that used the TAM to examine students' willingness to use LLMs, one line of research focused on exploring whether students are willing to use technology for the sake of learning[42,43]. Among several factors, the core drivers behind students' acceptance of LLMs like ChatGPT are perceived usefulness (PU) and perceived ease of use (PEOU). For example, students tend to believe that AI tools have significantly improved their learning efficiency (as per Tiwari et al.[44]) and have helped them with tasks like literature searches, assignment feedback, and knowledge integration. Of note, AI tools like ChatGPT are particularly effective in alleviating academic pressure[8].

Another body of research examines whether educators are willing to adopt technological tools to enhance teaching effectiveness[6]. It has been found that teachers, in particular, emphasize the educational value-add potential of LLMs like ChatGPT, such as optimizing course design and providing personalized feedback[45]. At the same time, ethical concerns emerge as a significant barrier, with educators expressing apprehension that AI tools may undermine students' critical thinking and exacerbate academic dishonesty[26]. Teachers' acceptance of ChatGPT is closely tied to their teaching roles: novice educators are more likely to rely on AI for teaching design, whereas experienced educators tend to view it as a supplementary tool[46].

A substantial body of existing research has demonstrated the applicability of the TAM to this study, as its effectiveness has been validated in prior educational context studies[47]. However, the application of TAM in exploring the usage of LLMs by teacher education students remains relatively underexplored. As future educators, teacher education students exhibit heightened sensitivity to the ethical risks posed by LLMs, such as data privacy concerns and academic integrity issues. As part of the student population, they are also directly engaged with the use of these technologies. Therefore, in order to facilitate the dynamic adaptation between technological system changes and complex individual behaviors, it is essential to thoroughly investigate the factors influencing teacher education students' willingness to use LLMs in specific contexts.

We extend the structural framework of the TAM to improve the model's explanatory power. TAM is extended by research findings involving individual characteristics, such as integrating self-efficacy, usage experience, and learning motivation. Overall, self-efficacy—the belief that an individual holds in his or her ability to use technology[48]—is commonly used to explain technology usage intention. A lack of confidence may prevent students from using technology, which is related to self-efficacy[49]. In turn, usage experience facilitates a "technology proficiency cycle" through cognitive accumulation. For example, García-Alonso et al.[50] established that digital proficiency has a strong relationship with technology adoption intention. Learning motivation is a critical factor that positively affects students' willingness to adopt artificial intelligence systems[51]. Notably, the unique nature of educational technology positions perceived risk as a key variable: technology users may express concerns over privacy risks and time-related risks associated with the use of such tools.

Model hypotheses

This section builds upon the classic TAM and, based on its core variables, introduces external variables such as self-efficacy (SE), experience (EX), subjective norms (SN), goal achievement (GA), perceived time risk (PTR), and perceived privacy risk (PPR). This results in the development of a more comprehensive theoretical framework, which serves as the foundation for the research hypotheses.

Self-efficacy (SE)

Albert Bandura defines "self-efficacy" (SE) as a person's belief in their in their capacity to overcome environmental challenges, stating that "the outcome depends on the adequacy of the behavior, and individuals rely on their self-assessment of efficacy when deciding which course of action to take"[52]. Accordingly, this study defines the SE of teacher education students as their subjective judgment and assessment of their ability or skills to successfully engage in LLM-assisted writing.

Studies have found that SE plays a crucial role in shaping individuals' cognitive evaluation of technology use, thereby influencing decision-making in technology adoption[53]. Consequently, SE has become a core construct in the extended TAM[21]. Studies on students' technological intentions have found a strong correlation between SE and SN[54,55]. SE further influences technology adoption intentions through GA[56]. In the case of teacher education students, their professional training necessitates the development of advanced writing skills. Those with higher SE are more likely to engage actively in writing practices, fostering the establishment of social support networks and cultivating a positive attitude toward assistive technologies, such as LLMs.

Moreover, teacher education students with strong SE often perceive themselves as capable of managing their time effectively[57], leading them to downplay concerns regarding the time costs associated with technology use. Furthermore, individuals with higher SE are more likely to adopt proactive measures to mitigate privacy risks[58], which may alleviate their concerns about data privacy breaches and reduce their PPR.

Building on this, we propose the following hypotheses:

H1 *The SE of fourth-year teacher education students significantly and positively influences the SN regarding the use of LLMs for writing.*

H2 *The SE of fourth-year teacher education students significantly and positively influences the GA in using LLMs for writing.*

H3 *The SE of fourth-year teacher education students significantly and positively influences the PTR when using LLMs for writing.*

H4 *The SE of fourth-year teacher education students significantly and positively influences the PPR when using LLMs for writing.*

Experience (EX)

Computer-related usage experience is typically defined as the degree of experience that users have with computer skills over time[59]. Accordingly, the EX related to LLMs writing can be defined as: individuals engage in activities such as writing with LLMs, and over time, accumulate the quantity and types of skills and knowledge related to the operation, adjustment, application, and optimization of the model.

EX is a frequently employed external variable in the TAM[60,61]. As individuals accumulate experience, the repository of past technology usage (Experience Repository) becomes a reference point for evaluating future behavior[62]. If students have been told by instructors or other students that using LLMs to produce strong writing outcomes echoes the "legitimacy of technology use" by social consensus, users' prior experience helps them distinguish and use LLM functions for writing tasks based on the objectives of the task[63].

Furthermore, previous research has also indicated that the more extensive the EX, the less the user perceived risk in the use of LLMs in writing[64]. On the one hand, experienced users build the skill to quickly produce content, optimize workflow, and break down tasks for better workflows. These skills drop perceived time risk by reducing delays when using these types of LLMs. On the other hand, those who are experienced tend to be more aware of privacy settings and are educated on how to avoid sharing such sensitive information and may as well use encryption tools to protect data thus reducing the perception of privacy risks.

To explore the relationships between experience, SN, GA, PTR, and PPR, we propose the following hypotheses:

H5 *The EX of fourth-year teacher education students using LLMs for writing significantly and positively influences SN.*

H6 *The EX of fourth-year teacher education students using LLMs for writing significantly and positively influences GA.*

H7 *The EX of fourth-year teacher education students using LLMs for writing significantly and negatively influences PTR.*

H8 *The EX of fourth-year teacher education students using LLMs for writing significantly and negatively influences PPR.*

Subjective norms (SN)

An internal psychological state, learning motivation encourages learners to engage in behaviors toward achieving learning goals[65,66]. According to K. Li[51], learning motivation refers to students' choice of certain learning activities and their consistent effort to carry them out, and its components include learning interest, goal achievement (GA), and subjective norms (SN). Given that a graduation thesis is typically written under external motivation, this study considers learning motivation to include subjective norms (SN)[67] and goal achievement (GA)[68].

Venkatesh[48] defines subjective norms (SN) as the social pressure perceived by individuals regarding whether or not to engage in a specific behavior. In the context of using LLMs assisted writing in teacher education, SN refers to the external pressures perceived by teacher education students when deciding whether to use LLMs for writing, influenced by the opinions of relevant people or groups.

Therefore, SN has a significant impact on writing behavioral intentions[69]. Different mentors hold different opinions on the use of LLMs[70,71]. Some encourage rational use by students, while others are concerned about academic independence and creativity. Previous studies have also shown that SN positively influences people's technology adoption intentions[72,73]. Furthermore, subjective norms also influence perceived usefulness and perceived ease of use[74]. When significant others actively endorse the value of LLMs in writing, students are more likely to enhance their perception of its usefulness. Additionally, if influential individuals recommend using LLMs and there are existing successful writing experiences, student teachers are more likely to perceive the technology as easy to learn and use, thereby reducing concerns about learning costs and increasing their perception of ease of use. Based on this, we propose the following hypotheses:

H9 *The SN of fourth-year teacher education students significantly and positively influence their BI to use LLMs for writing.*

H10 *The SN of fourth-year teacher education students significantly and positively influence their GA in using LLMs for writing.*

H11 *The SN of fourth-year teacher education students significantly and positively influence their PEOU in using LLMs for writing.*

Goal achievement (GA)

Learning motivation is an internal state or condition that seeks the meaning of behavior and strives to gain benefits from these actions[75]. Goal achievement (GA), as an important form of learning motivation, typically refers to the drive to exert effort to accomplish specific objectives[68], often driven by the desire to attain external rewards. In this study, GA denotes the extrinsic motivation of teacher education students to accomplish writing-related objectives, such as enhancing writing efficiency, improving paper quality, reducing writing time, and fulfilling graduation requirements.

GA, as the core motivators of individual behavior[76], serve as critical antecedents to technology usage behavior[77,78]. Research on AI adoption found that GA strongly predicts both PEOU and PU[51]. As LLMs enable faster completion of writing goals, they can reduce stress and anxiety during the writing process. This study focuses on teacher education students approaching graduation, considering their goal of completing a thesis. When they aim to use a LLM to quickly finish their writing, they will primarily focus on whether the tool is useful and easy to use.

Therefore, the following hypotheses emerge:

H12 *GA of fourth-year teacher education students significantly and positively influence the PU of using LLMs for writing.*

H13 *GA of fourth-year teacher education students significantly and positively influence the PEOU of using LLMs for writing.*

Perceived time risk (PTR)

Perceived risk is typically explained as a subjective judgment of risk characteristics and severity[79]. A study on mobile travel reservations by Park and Tussyadiah[80] identified seven types of perceived risks. These include time risk, financial risk, performance risk, privacy risk, security risk, psychological risk, physical risk, and device risk. Perceived time risk (PTR), as one dimension of perceived risk that influences individual decision-making[81,82], refers to the risk individuals perceive in terms of time and effort expenditure during product usage[83,84].

On the one hand, when generating text, LLMs may produce outputs that do not align with expected language style or structural logic[85–87], requiring additional time to correct writing errors. On the other hand, although LLM-generated content is efficient, issues such as login failures and network restrictions may cause delays, further increasing the time burden[88,89].

Therefore, in the context of writing with LLMs, PTR can be understood as the time and effort wasted when teacher education students fail to achieve their expected writing goals. When individuals perceive a high time risk, it may negatively impact their PU and PEOU of the technology. Based on this, the following hypotheses are proposed:

H14 *The PTR of fourth-year teacher education students significantly and negatively influences the PU of using LLMs for writing.*

H15 *The PTR of fourth-year teacher education students significantly and negatively influences the PEOU of using LLMs for writing.*

Perceived privacy risk (PPR)

Perceived privacy risk (PPR) is a key dimension of risk perception[90]. It denotes the uncertainty regarding the adverse outcomes linked to using a particular product or service, especially the potential loss resulting from the exposure of personal information[91]. In this study, PPR describes users' awareness of the potential negative consequences related to sharing personal information while using LLMs for text generation.

Writing often involves extensive professional data, research findings, personal opinions, original thoughts, or unpublished experimental data[92–94]. However, LLMs may store users' input data for model improvement or optimization, leading users to worry about improper storage or information leakage when inputting sensitive information[95–97].

PPR may increase time investment, prolong decision-making processes, and lead to repetitive tasks, significantly amplifying the intensity and scope of PTR[98,99]. When facing writing pressures, users who believe that LLMs can substantially enhance academic writing efficiency or quality may be willing to tolerate certain privacy risks[100]. Moreover, if LLMs are easy to use and allow users to quickly achieve desired results, they may overlook privacy risks during use[101]. Furthermore, research has shown that perceived risks influence individuals' BI[102]. PPR, in particular, trigger concerns related to data security, academic integrity, and professional ethics, thereby impacting the willingness to use such technologies. This, in turn, leads to avoidance behaviors among fourth-year teacher education students when it comes to utilizing LLMs for writing tasks. Building on the above, the hypotheses are as follows:

H16 *The PPR of fourth-year teacher education students significantly and positively influences their PTR when using LLMs for writing.*

H17 *The PPR of fourth-year teacher education students significantly and negatively influences their PU of using LLMs for writing.*

H18 *The PPR of fourth-year teacher education students significantly and negatively influences their PEOU of using LLMs for writing.*

H19 *The PPR of fourth-year teacher education students significantly and negatively influence their BI of using LLMs for writing.*

Perceived usefulness (PU)

Perceived usefulness (PU) is key in technology adoption, reflecting an individual's belief in a new technology's ability to meet their needs[17]. In the context of teacher education students using LLMs for writing, PU can be defined as the subjective perception that using LLMs for writing enhances the efficiency of writing, reduces writing difficulty, and improves the overall quality of the paper or the ability to accomplish tasks.

Studies have shown that PU positively influences technology acceptance[103–105]. In studies on e-learning intentions among university students[38], virtual laboratory usage intentions[106], and K12 students' intentions to use tablets[107], PU influences BI through ATU.

The LLMs can assist individuals in writing efficiently[108]. While improving collaboration efficiency, individuals are likely to develop more positive views of the LLMs[109]. If teacher education students perceive that LLMs can significantly improve writing efficiency, enhance quality, and simplify the writing process, they are more inclined to have a favorable attitude toward using them. Therefore, the following hypotheses emerge:

H20 *PU among fourth-year teacher education students significantly and positively influences their ATU of using LLMs for writing.*

Perceived ease of use (PEOU)

Perceived ease of use (PEOU) is the perception of how easy or difficult it is to operate a product or system[17]. In this study, it is understood as the extent to which teacher education students perceive the ease of operating LLMs to assist with writing.

In the TAM, PEOU is typically seen as affecting one's PU and ATU in a technological system[17,48]. Research on the educational social networking site Edmodo showed that PEOU directly predicted PU[110]. As a deep neural network model with a vast number of parameters, LLMs support text generation, language translation, sentence rewriting, and grammar checking, enabling users to obtain desired content[88,111] while enhancing the multi functionality and convenience of writing. When fourth-year teacher education students use LLMs for writing, if they perceive the tool as easy to use, it will reduce their learning costs and mental burden, thereby enhancing their perception of its usefulness.

Research on AI usage intentions suggests that PEOU affects both PU and ATU, which subsequently influence BI[13,112]. If teacher education students find LLMs simple to use for writing, their adoption likelihood increases. From this, the following hypotheses emerge:

H21 *PEOU among fourth-year teacher education students significantly and positively affects their PU of using LLMs for writing.*

H22 *PEOU among fourth-year teacher education students significantly and positively affects their ATU toward LLMs for writing.*

Attitude toward using (ATU)

Attitude toward using (ATU) is a person's long-term favorable or unfavorable perception of a particular object or behavior[67]. An individual's attitude not only reflects internal feelings about external objects but also reflects their favorable or unfavorable perceptions of using technology[113]. This study defines ATU as teacher education students' favorable or unfavorable emotional reactions to using LLMs for writing tasks. This ATU reflects their internal perceptions of the LLM's utility, ease of use, and effectiveness in academic writing. It also reflects their overall evaluation of the possible benefits and drawbacks of using the technology (such as time savings or concerns about privacy). A positive ATU typically enhances their willingness to use the technology, while a negative ATU may hinder its adoption.

Research shows that ATU directly influences doctoral students' BI to use ChatGPT in writing[41]. A study found that the BI to adopt ChatGPT among higher education students in Thailand, is influenced by their ATU[105]. When ATU and BI are closely connected, consistency between them is observed. This means that under favorable conditions, ATU can influence behavioral intention (BI) and, eventually, result in the behavior itself[60,114].

Given the efficiency, flexibility, and ease of use demonstrated by LLMs in writing, individuals may develop positive ATU. These ATU encompass subjective evaluations and the resulting behavioral tendencies, which in turn increase individuals' willingness and behavior. To confirm the predictive role of ATU on BI in this study, the following hypothesis is proposed:

H23 *The ATU of fourth-year teacher education students positively influences their BI toward using LLMs for writing.*

In summary, drawing on prior literature and theoretical analysis, this research integrates the TAM to develop a comprehensive conceptual model (see Fig. 2) that considers individual factors, external environment, and technological characteristics.

Methodology

Sample and data collection

The questionnaire for this study was collected through the "Wenjuanxing" platform to ensure a high response rate within a short period. Before the formal survey, we provided a detailed explanation of the concept of "large language models (LLMs)" in the questionnaire instructions to help respondents better understand the relevant content and answer the questionnaire efficiently. In addition, informed consent was obtained from all respondents, ethical approval was obtained from the Academic Committee of the China Institute of Rural Education Development of Northeast Normal University, and participants were assured of their right to anonymity. Furthermore, the questionnaire included a screening mechanism that asked respondents about

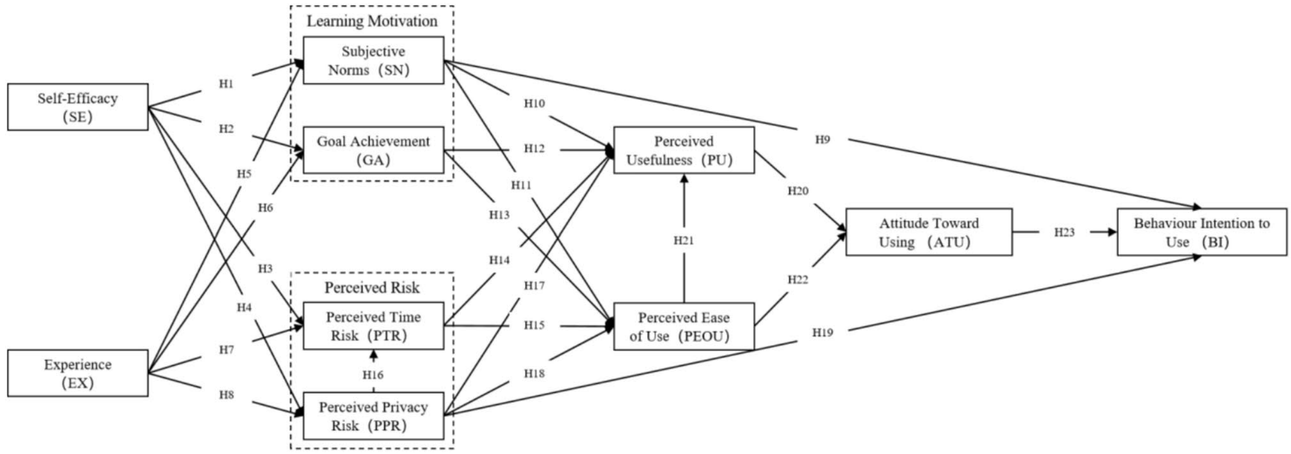

Fig. 2. Conceptual model and hypotheses.

the frequency of using LLMs for writing. If a respondent selected "Never", their responses were excluded from further analysis in the study.

A total of 610 questionnaires were initially received. After excluding invalid submissions caused by missing data, identical ratings across all items, or completion times under 120 s, 552 valid submissions remained, yielding a valid rate of 90.49%. According to Hair et al.[115], the minimum required sample size is tenfold the measurement items of the most complex factor. Therefore, the 552 valid questionnaires gathered meet the necessary requirements for the sample. Based on this, we converted the valid questionnaires into an SPSS data sheet and encoded them according to the sequence of the hypothesis model.

Measurement instrument

The survey questionnaire in this study consists of two sections: The initial section gathers student demographics, covering sample characteristics (e.g., gender, place of origin, discipline), as well as questions related to the use of LLMs (usage type, frequency of use). The second section focuses on analyzing the key factors in the model to comprehensively assess the various dimensions influencing students' use of LLMs for writing. These factors include Self-efficacy (SE), Experience (EX), Subject norms (SN), Goal achievement (GA), Perceived time risk (PTR), Perceived privacy risk (PPR), Perceived usefulness (PU), Perceived ease of use (PEOU), Attitude toward using (ATU), and Behavioral intention to use (BI). These indicators help to systematically understand teacher education students' acceptance and willingness to use LLMs for writing.

Except for the demographic information questionnaire, all items were rated using a five-point Likert scale, ranging from "Strongly Disagree (1)" to "Strongly Agree (5)". Prior to the formal distribution of the questionnaire, a pilot study was conducted at Northeast Normal University (Northeast China), Qujing Normal University (Southwest China), and Suqian University (Eastern China) to ensure the feasibility and clarity of the questionnaire for respondents. Based on the feedback received, we revised the items in the PPR, PTR, EX, and GA sections to enhance clarity. Additionally, the number of items in the EX section was reduced from five to four, while the ATU (Attitude Toward Use) and GA sections were reduced from six to four items to improve measurement accuracy and reliability. Before completing the questionnaire, students received a brief introduction to LLMs, along with an explanation of the background and objectives of the study. They were then asked to answer the questions based on their genuine opinions. The detailed content of the questionnaire is presented in Table 1.

Date analysis

This study used SPSS 27.0 and AMOS 28.0 for statistical analysis. Descriptive analysis was conducted using SPSS 27.0, and item reliability was assessed to ensure result consistency, stability, and accuracy. Additionally, skewness and kurtosis values for all items are computed[123] to test whether the collected data meet the normal distribution requirements. AMOS 28.0 analyzes both the measurement and structural models[124]. The measurement model defines the associations between latent and observed variables, whereas the structural model identifies the causal links among latent variables. Since this study extends the existing TAM model and incorporates various constructs and indicators, AMOS software is used to build the SEM and assess the validity of the theoretical assumptions.

Results

Participants

The final analysis used 552 valid responses, with descriptive statistics of the questionnaire sample's basic information shown in Table 2. Among the respondents, 142 (25.72%) were male and 410 (74.28%) were female. Regarding the geographical origin of the respondents, 39.86% came from urban high schools, 50.72% from suburban high schools, and 9.42% from rural high schools. The participants were from 16 different majors. Regarding usage frequency, the majority of respondents (193, 34.96%) used LLMs nearly every day, 17.57% (97

Constructs	Items	References
Self-Efficacy (SE)	Even without assistance, I am confident in using LLMs to complete academic paper writing	[116,117]
	I have sufficient skills to use LLMs for academic paper writing	
	I am confident in finding solutions when encountering issues while using LLMs for writing	
	I am confident that I can find writing information in the LLMs model	
Experience (EX)	Prior to this, I frequently used LLMs	[41,118]
	Prior to this, I was able to use LLMs with ease	
	Prior to this, I felt comfortable using LLMs	
	Prior to this, I was able to construct specific input prompts	
Subjective norms (SN)	The individuals who impact my actions encouraged me to adopt LLMs for paper writing	[48,72]
	The individuals who affect my behavior think using LLMs for academic writing benefits my learning	
	The individuals who matter to me encouraged me to use LLMs for paper writing	
	The people who are important to me believe that using LLMs for academic writing is helpful for my learning	
Goal achievement (GA)	Using LLMs is essential for reaching my paper writing goals	[51,55,119]
	Using LLMs is efficient because it's available whenever and wherever I need it	
	Using LLMs is important for saving time in academic paper writing	
	Using LLMs is convenient because I can access them at any time and from any location	
Perceived time risk (PTR)	Using LLMs may result in poor academic writing performance, leading to wasted time	[82,83,120]
	Using LLMs might waste a significant amount of time correcting writing errors, causing inconvenience	
	Using (and configuring) LLMs requires an investment of my time, which could pose certain risks	
	Learning how to use (and configuring) LLMs may consume a considerable amount of time	
Perceived privacy risk (PPR)	In general, providing writing information to LLMs may pose privacy risks	[82,91]
	Providing writing information to LLMs may likely lead to potential risks or losses	
	Providing writing information to LLMs may bring about many unexpected issues	
	Providing writing information to LLMs involves too much uncertainty	
Perceived usefulness (PU)	Using LLMs has improved the efficiency of my paper writing	[17,48,121]
	Using LLMs can help me improve the quality of my paper writing	
	Using LLMs has made paper writing much easier	
	Using LLMs in paper writing is very helpful	
Perceived ease of use (PEOU)	Learning to use/operate LLMs is very easy	[17,48,121]
	Using LLMs is neither complex nor difficult to understand	
	The skills required to use LLMs are basic	
	Using LLMs to obtain information related to paper writing is very simple	
Attitude toward using (ATU)	Using LLMs is appealing to me	[67,113]
	I am inclined to use the LLMs	
	Using LLMs feels great to me	
	Overall, I view using LLMs favorably	
Behaviour intention to use (BI)	I will use LLMs more in my future paper writing	[48,67,122]
	I plan to use LLMs to assist with my paper writing	
	I would recommend LLMs to my friends/classmates	
	I will use LLMs frequently in the future	

Table 1. Items and constructs of the scale construct items reference.

respondents) used them daily, 31.52% (174 respondents) used them once or twice a week, and only 88 (15.94%) used them once or twice a month. Among the commonly used LLMs, ERNIE Bot and Doubao were in the first tier, used by 305 (55.25%) and 285 (51.63%) respondents, respectively. ChatGPT (177, 32.07%), Kimi (174, 31.52%), GLM-4 (145, 26.27%), and SparkDesk (137, 24.82%) were in the second tier.

Measurement model

Subsequently, we conducted reliability and validity analysis of the collected data using SPSS 27.0. To examine the consistency and reliability of the questionnaire, the study utilized Cronbach's Alpha for reliability analysis[125]. The results, shown in Table 3, indicate that the Cronbach's Alpha values ranged from 0.778 to 0.855, all exceeding the 0.7 threshold, suggesting that the scale has high internal consistency. Additionally, the Composite Reliability (CR) ranged from 0.812 to 0.916[126], also surpassing the recommended 0.7 standard, further confirming that the research model demonstrates strong internal consistency.

Additionally, we conducted validity testing for the questionnaire. As presented in Table 3, the results demonstrate that the standardized factor loadings for the measurement items corresponding to the 10 dimensions in the research model range from 0.652 to 0.894[126], all of which exceed the recommended value of

Demographics	Category	N = 552	Percentage (%)
Gender	Male	142	25.72
	Female	410	74.28
Place of origin of high school students	Cities	220	39.86
	Counties	280	50.72
	Towns	52	9.42
Subject category	Language	47	8.51
	Math	41	7.43
	English	40	7.25
	History	30	5.43
	Geography	35	6.34
	Physics	31	5.62
	Chemistry	29	5.25
	Politics	27	4.89
	Biology	19	3.44
	Art	24	4.35
	Music	27	4.89
	Physical Education	32	5.80
	Education	35	6.34
	Preschool Education	52	9.42
	Elementary Education	55	9.96
	Psychology	28	5.07
Frequency of use of LLM	Never	0	0.00
	Once or twice a month	88	15.94
	Once or twice a week	174	31.52
	Almost every day	193	34.96
	Every day	97	17.57
Common large language model	Qwen	84	15.22
	ERNIE Bot	305	55.25
	GLM-4	145	26.27
	SparkDesk	137	24.82
	Pangu	53	9.60
	Chatgpt	177	32.07
	Doubao	285	51.63
	Kimi	174	31.52
	Hunyuan AI	25	4.53
	Tiangong	39	7.07

Table 2. Sampling.

0.5 and are statistically significant. The Average Variance Extracted (AVE) for each variable is also above the 0.5 threshold[126], suggesting that the model demonstrates high convergent validity.

Fornell and Larcker[126] stated that when a variable's AVE exceeds the squared Pearson correlations with any other variable, it signifies strong discriminant validity. Accordingly, the AVE for each latent variable was calculated. The results (see Table 4) show that the measurement of each latent variable in this study exhibits good discriminant validity.

In addition, we conducted a correlation analysis (Table 5). The Pearson correlation coefficients between variables reflect the linear relationships between them. The correlation coefficients range from 0.088 (EX and PPR) to 0.658 (PTR and PPR), showing that most variables are significantly correlated within the model.

Subsequently, we performed a descriptive analysis with SPSS 27.0. Table 6 presents the results, indicating that variable means ranged from 2.835 to 4.112. The scale adopted a 1–5 Likert-type scoring system, indicating that the participants' overall acceptance of educational LLMs was above average.

Skewness and kurtosis were used to test the normality of the data for each indicator. Kline[127] suggests that if the skewness coefficient's absolute value is below 3 and the kurtosis coefficient's absolute value is below 8, the data can be considered approximately normally distributed. Table 6 shows that all skewness and kurtosis values fall within the standard range, suggesting an approximately normal distribution and ensuring the validity of subsequent statistical analyses.

Construct	Items	Factor Loading	CR(>0.70)	AVE(>0.50))	Cronbach'sa(>0.70)
Self-Efficacy (SE)	SE1	0.813	0.882	0.651	0.838
	SE2	0.804			
	SE3	0.804			
	SE4	0.823			
Experience (EX)	EX1	0.787	0.818	0.531	0.793
	EX2	0.736			
	EX3	0.733			
	EX4	0.652			
Subjective norms(SN)	SN1	0.707	0.842	0.572	0.806
	SN2	0.766			
	SN3	0.703			
	SN4	0.841			
Goal achievement (GA)	GA1	0.790	0.842	0.572	0.816
	GA2	0.727			
	GA3	0.773			
	GA4	0.734			
Perceived time risk(PTR)	PTR1	0.817	0.876	0.639	0.828
	PTR2	0.775			
	PTR3	0.804			
	PTR4	0.801			
Perceived privacy risk(PPR)	PPR1	0.855	0.916	0.731	0.855
	PPR2	0.836			
	PPR3	0.894			
	PPR4	0.833			
Perceived usefulness(PU)	PU1	0.838	0.876	0.638	0.829
	PU2	0.766			
	PU3	0.747			
	PU4	0.840			
Perceived (PEOU)	PEOU1	0.719	0.812	0.519	0.778
	PEOU2	0.725			
	PEOU3	0.730			
	PEOU4	0.708			
Attitude toward using (ATU)	ATU1	0.804	0.898	0.687	0.839
	ATU2	0.841			
	ATU3	0.795			
	ATU4	0.874			
Behaviour intention to use (BI)	BI1	0.820	0.883	0.654	0.831
	BI2	0.821			
	BI3	0.755			
	BI4	0.837			

Table 3. Results of measurement model.

Structural equation modeling

After conducting reliability, validity, and normality tests on the measurement model, we constructed the SEM for the research hypotheses using AMOS software. The model was further evaluated according to the standards set by Hu and Bentler[128]. Table 7 shows that the model's indices all align with the recommended standards: CMIN/DF = 2.008 (< 3), $p = 0.00000$, RMSEA = 0.043 (< 0.05;[129]), IFI = 0.944 (> 0.90;[130]), TLI = 0.938 (> 0.90;[130]), and CFI = 0.943 (> 0.90;[131]). The numerical results above demonstrate that all indicators meet the acceptable standards, with the model showing a good overall fit.

Path analysis

The hypothesis path analysis outcomes proposed in this research are presented in Table 8 and Fig. 3. Unexpectedly, EX had no significant effect on PPR ($\beta = -0.069$, $p > 0.05$), suggesting that EX was not a key factor in predicting students' PPR, thereby not supporting H8. Furthermore, PTR's direct effect on PEOU was not significant ($\beta = -0.225$, $p > 0.05$), indicating that H15 was not supported. With the exception of H8 and H16, all other hypotheses were supported.

Variables	SE	EX	SN	GA	PTR	PPR	PU	PEOU	ATU	BI
SE	0.687									
EX	0.522	0.519								
SN	0.382	0.481	0.638							
GA	− 0.341	− 0.467	− 0.309	0.731						
PTR	0.358	0.513	0.330	− 0.469	0.654					
PPR	− 0.438	− 0.420	− 0.459	0.737	−0.444	0.639				
PU	0.453	0.398	0.401	− 0.207	0.303	− 0.305	0.572			
PEOU	0.368	0.511	0.499	− 0.387	0.503	− 0.442	0.520	0.572		
ATU	0.159	0.283	0.408	− 0.080	0.256	− 0.191	0.529	0.570	0.531	
BI	0.498	0.447	0.381	− 0.202	0.347	− 0.289	0.404	0.457	0.417	0.651
AVE values square root	0.829	0.720	0.799	0.855	0.809	0.799	0.756	0.756	0.729	0.807

Table 4. Discriminant validity and the correlations of variables (Fornell–Larcker criterion). The values above the diagonal represent the AVE of the variables and the data in the lower left corner are the correlation coefficients. SE, Self-Efficacy; EX, Experience; SN, Subjective Norms; GA, Goal Achievement; PTR, Perceived Time Risk; PPR, Perceived Privacy Risk; PU, Perceived Usefulness; PEOU, Perceived Ease of Use; ATU, Attitude Toward Using; BI, Behaviour Intention to Use.

Variables	SE	EX	SN	GA	PTR	PPR	PU	PEOU	ATU	BI
SE	1									
EX	0.363**	1								
SN	0.402**	0.482**	1							
GA	0.342**	0.437**	0.431**	1						
PTR	− 0.257**	− 0.173**	− 0.374**	− 0.267**	1					
PPR	− 0.183**	− 0.088*	− 0.333**	− 0.186**	0.658**	1				
PU	0.343**	0.364**	0.438**	0.353**	− 0.408**	− 0.272**	1			
PEOU	0.377**	0.251**	0.414**	0.335**	− 0.354**	− 0.397**	0.406**	1		
ATU	0.443**	0.150**	0.316**	0.395**	− 0.384**	− 0.301**	0.337**	0.444**	1	
BI	0.302**	0.225**	0.425**	0.259**	− 0.385**	− 0.421**	0.291**	0.435**	0.314**	1

Table 5. Pearson correlation coefficient. **Correlation is significant at the 0.01 level (one-tailed). *Correlation is significant at the 0.05 level (one-tailed). SE, Self-Efficacy; EX, Experience; SN, Subjective Norms; GA, Goal Achievement; PTR, Perceived Time Risk; PPR, Perceived Privacy Risk; PU, Perceived Usefulness; PEOU, Perceived Ease of Use; ATU, Attitude Toward Using; BI, Behaviour Intention to Use.

In the hypothesis paths H1-H4, SE was found to have a significant positive impact on SN ($\beta = 0.246$, $p < 0.001$), GA ($\beta = 0.194$, $p < 0.001$), PTR($\beta = -0.098$, $p < 0.05$) and PPR ($\beta = -0.231$, $p < 0.001$). In hypothesis paths H5-H8, EX exerted a significant positive effect on SN ($\beta = 0.586$, $p < 0.001$) and GA ($\beta = 0.554$, $p < 0.001$), while demonstrating a notable negative effect on PTR ($\beta = -0.154$, $p < 0.01$). In hypothesis paths H9-H11, SN significantly influenced BI ($\beta = 0.412$, $p < 0.001$), GA ($\beta = 0.287$, $p < 0.001$) and PEOU ($\beta = 0.235$, $p < 0.001$), indicating that SN is a key driver of BI.

In other paths, GA significantly influenced PU ($\beta = 0.164$, $p < 0.01$) (H12) and PEOU ($\beta = 0.164$, $p < 0.001$) (H13). PTR significantly affected PU ($\beta = -0.393$, $p < 0.001$) (H14), indicating that PTR is a major barrier to PU. Additionally, PPR significantly influenced PTR ($\beta = 0.589$, $p < 0.001$) (H16), PU ($\beta = 0.152$, $p < 0.05$) (H17), and negatively affected PEOU ($\beta = -0.188$, $p < 0.001$) (H18), BI ($\beta = -0.285$, $p < 0.001$) (H19). In the basic hypothesis model of the TAM, PU significantly influenced ATU ($\beta = 0.186$, $p < 0.001$) (H20), PEOU significantly affected both PU ($\beta = 0.347$, $p < 0.001$) (H21) and ATU ($\beta = 0.771$, $p < 0.001$) (H22), while ATU significantly impacted BI ($\beta = 0.119$, $p < 0.01$) (H23).

Discussion and implications

Research findings

As the application of LLMs in education continues to deepen, the academic community has increasingly focused on the differentiated adoption mechanisms across various user groups and contexts. The TAM, a classical theoretical framework for explaining individual technology adoption behavior[17,132], provides a critical foundation for this study. This research examines the higher education context in China, targeting fourth-year teacher education students who are about to enter the teaching profession, to explore key factors influencing their adoption of LLMs for academic writing. By integrating the core constructs of TAM with external variables and employing structural equation modeling for hypothesis testing, this study yields several key findings:

Variable	Mean	Standard deviation	Skewness	Kurtosis
SE1	3.726	1.102	− 0.715	− 0.155
SE2	3.649	1.084	− 0.639	− 0.140
SE3	3.833	1.072	− 0.828	0.108
SE4	3.784	1.094	− 0.976	0.494
EX1	3.908	0.987	− 0.679	− 0.186
EX2	3.993	0.951	− 0.711	− 0.060
EX3	4.112	0.834	− 0.760	0.270
EX4	3.902	0.936	− 0.670	0.068
SN1	3.480	0.860	− 0.221	− 0.101
SN2	3.513	0.906	− 0.354	0.023
SN3	3.411	0.893	− 0.275	− 0.122
SN4	3.533	0.903	− 0.261	− 0.078
GA1	3.793	1.007	− 0.584	− 0.145
GA2	3.774	1.025	− 0.703	0.123
GA3	3.922	0.984	− 0.795	0.348
GA4	3.841	1.019	− 0.896	0.496
PTR1	2.861	0.979	− 0.067	− 0.665
PTR2	2.835	1.015	− 0.072	− 0.498
PTR3	2.964	1.015	− 0.157	− 0.443
PTR4	2.848	1.041	0.066	− 0.450
PPR1	3.219	1.235	− 0.127	− 0.967
PPR2	3.069	1.195	− 0.037	− 0.927
PPR3	3.277	1.278	− 0.174	− 1.054
PPR4	3.132	1.188	− 0.140	− 0.865
PU1	3.850	1.039	− 0.856	0.320
PU2	3.721	1.046	− 0.693	0.046
PU3	3.775	1.076	− 0.675	− 0.132
PU4	3.703	1.077	− 0.656	− 0.150
PEOU1	3.799	0.838	− 0.146	− 0.691
PEOU2	3.716	0.846	− 0.162	− 0.599
PEOU3	3.726	0.785	− 0.086	− 0.485
PEOU4	3.634	0.824	− 0.112	− 0.519
ATU1	3.743	1.112	− 0.766	− 0.117
ATU2	3.759	1.113	− 0.852	0.119
ATU3	3.795	1.036	− 0.849	0.349
ATU4	3.692	1.116	− 0.851	0.112
BI1	3.605	1.081	− 0.653	− 0.085
BI2	3.721	1.152	− 0.849	− 0.033
BI3	3.763	1.064	− 0.767	0.053
BI4	3.524	1.166	− 0.546	− 0.520

Table 6. Normality test results for measurement items. SE, Self-Efficacy; EX, Experience; SN, Subjective Norms; GA, Goal Achievement; PTR, Perceived Time Risk; PPR, Perceived Privacy Risk; PU, Perceived Usefulness; PEOU, Perceived Ease of Use; ATU, Attitude Toward Using; BI, Behaviour Intention to Use.

Norm	Reference standard	Data results
CMIN/DF	A value between 1 and 3 is excellent, and between 3 and 5 is good	2.008
RMSEA	A value below 0.05 is excellent, while below 0.08 is good	0.043
IFI	A value greater than 0.9 is considered excellent, while a value greater than 0.8 is regarded as good	0.944
TLI	A value greater than 0.9 is considered excellent, while a value greater than 0.8 is regarded as good	0.938
CFI	A value greater than 0.9 is considered excellent, while a value greater than 0.8 is regarded as good	0.943

Table 7. Model fit checklist.

Hypothesis	Relationship	Estimate	S.E	C.R	*p*	Result
H1	SE→SN	0.246	0.040	6.173	***	Support
H2	SE→GA	0.194	0.041	4.712	***	Support
H3	SE→PTR	−0.098	0.038	−2.552	*	Support
H4	SE→PPR	−0.231	0.059	−3.919	***	Support
H5	EX→SN	0.586	0.067	8.710	***	Support
H6	EX→GA	0.554	0.070	7.869	***	Support
H7	EX→PTR	−0.154	0.057	−2.711	**	Support
H8	EX→PPR	−0.069	0.087	−0.793	0.427	Not Support
H9	SN→BI	0.412	0.053	7.721	***	Support
H10	SN→PU	0.287	0.061	4.680	***	Support
H11	SN→PEOU	0.235	0.039	5.987	***	Support
H12	GA→PU	0.164	0.059	2.795	**	Support
H13	GA→PEOU	0.164	0.039	4.207	***	Support
H14	PTR→PU	−0.393	0.076	−5.162	***	Support
H15	PTR→PEOU	−0.025	0.050	−0.512	0.608	Not Support
H16	PPR→PTR	0.589	0.039	15.292	***	Support
H17	PPR→PU	0.152	0.063	2.401	*	Support
H18	PPR→PEOU	−0.188	0.041	−4.561	***	Support
H19	PPR→BI	−0.285	0.038	−7.485	***	Support
H20	PU→ATU	0.186	0.054	3.451	***	Support
H21	PEOU→PU	0.347	0.093	3.714	***	Support
H22	PEOU→ATU	0.771	0.095	8.086	***	Support
H23	ATU→BI	0.119	0.040	2.982	**	Support

Table 8. Results of structural model and path coefficients. * = $p < .05$, ** = $p < .01$, *** = $p < .001$. SE, Self-Efficacy; EX, Experience; SN, Subjective Norms; GA, Goal Achievement; PTR, Perceived Time Risk; PPR, Perceived Privacy Risk; PU, Perceived Usefulness; PEOU, Perceived Ease of Use; ATU, Attitude Toward Using; BI, Behaviour Intention to Use.

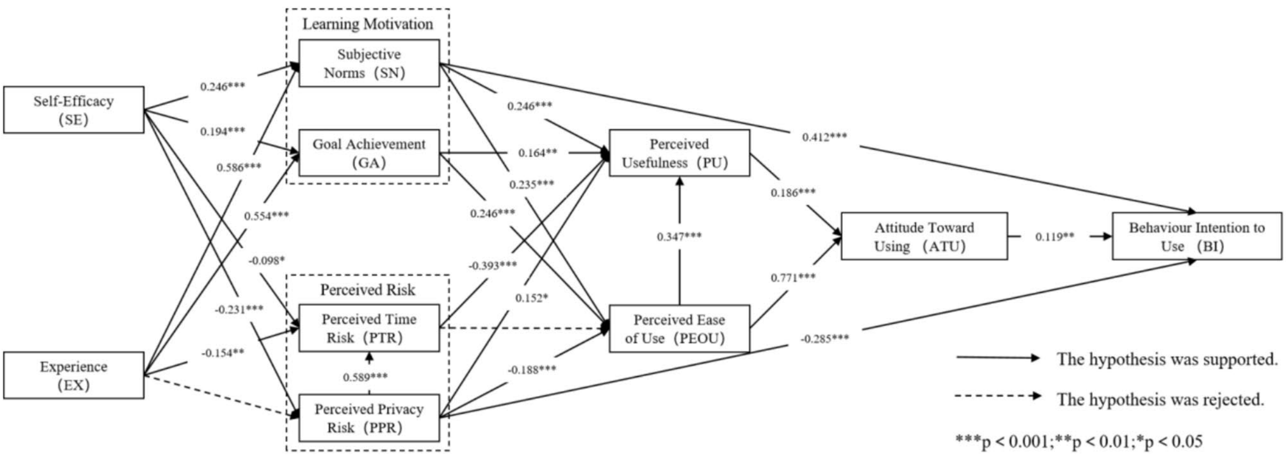

Fig. 3. Results of the structural model.

This study empirically reveals that subjective norms significantly positively predict teacher education students' behavioral intentions to use LLMs for writing (H9). This finding aligns with the consensus in the field of educational technology adoption: in the highly professionalized group of teacher education students, external normative pressures play a particularly prominent role in shaping their technology usage decisions[133,134]. In this context, subjective norms refer to the extent to which teacher education students perceive the technology usage expectations of important reference groups (significant referents) and their tendency to comply with these expectations in their behavioral decisions. The mechanism of this influence can be systematically explained through a multidimensional theoretical framework. From a cultural psychology perspective, Geert[135] cultural dimensions theory provides a critical lens for interpreting the group characteristics of Chinese teacher education students. The collectivist tendencies in Chinese society incline individuals to prioritize "group consensus" over independent technological judgment when making adoption decisions. Specifically, in the case of teacher education students, the continued immersion in the "teacher community" culture during their professional development, along with peer evaluation systems, mentor authority, and the technology usage norms in future professional contexts, collectively create a powerful normative pressure field.

It is important to note that this normative pressure not only drives behavior but also becomes an integral component of professional identity formation. Communication has shown that teacher education students perceive the use of LLMs for writing as being under normative tension between instrumental rationality (enhancing writing efficiency) and value rationality (adhering to academic norms)[136]. A slight misstep could impact their academic reputation and career development. As a result, teacher education students tend to adhere to norms in order to gain positive self-evaluation and social recognition. This finding highlights the importance of subjective norms in shaping LLMs usage behavior. In the process of teacher education, measures such as building exemplary application communities, strengthening the technological leadership of mentor teams, and establishing collective usage norms can effectively enhance the positive guiding role of subjective norms. Compared to mere technical training, fostering group dynamics that align with the professional socialization needs of teacher education students can facilitate the shift in technology acceptance from "external compliance" to "internal identification".

This study validates the hypothesis (H22) that perceived ease of use has a more significant impact than perceived usefulness on attitudes toward the use of LLMs. This finding aligns with the conclusions of Alshurideh et al.[137] regarding the use intention of ChatGPT. From the perspective of cognitive resource allocation, Sweller[138] cognitive load theory provides theoretical support for this phenomenon: when individuals face new technology, they must simultaneously manage intrinsic cognitive load (arising from the complexity of the task itself) and extraneous cognitive load (stemming from external factors such as interface design). When the combined load exceeds the user's cognitive resource threshold, it directly affects their utility evaluation process. According to Karahanna and Straub[139], stage-based model of technology adoption, users exhibit a low tolerance for operational barriers during the early stages of technology interaction. If a system presents high usability barriers (e.g., complex operating procedures, unclear functional guidance), even if the potential utility is significant, users may abandon further exploration due to initial cognitive overload. This phenomenon is especially prominent in the field of educational technology, where teacher education students, as prospective educators, are often closely linked to the time costs of their teaching practices. Therefore, technology developers should pay particular attention to optimizing the "first-use experience", such as designing preset writing template libraries or one-click functions to enhance the initial user experience. Training designers can adopt the principle of progressive disclosure, offering a simplified version of core functions in the early stages, and gradually introducing advanced features once users have established basic proficiency.

Furthermore, this study delves into the influence mechanism of perceived risk on technology adoption intention. Empirical results indicate that perceived time risk has a significant negative effect on perceived usefulness (H14), aligning with Paul A[140], who identified perceived risk as a precursor to perception-related constructs. From the perspective of cognitive load theory, when users anticipate excessive time costs in utilizing LLMs—such as repeatedly correcting logical inconsistencies or mismatched styles—their working memory resources become occupied with non-essential tasks, leading to cognitive overload and diminishing their evaluation of technological utility[141]. For teacher education students, time serves as a crucial dimension in assessing technological benefits[9,142]. The study also reveals that while ChatGPT effectively addresses most issues, its performance in processing emotional texts remains suboptimal[143]. Participants had to engage in multiple iterations due to semantic ambiguity in model outputs, resulting in a cognitive perception of "technological efficacy devaluation". Given this, mitigating perceived time risk is essential. Developers should focus on optimizing the accuracy of initial model outputs and establishing a reinforcement learning-based user feedback loop to enhance users' marginal perception of technology usefulness.

In the dimension of privacy risk, the study reveals that the inhibitory effect of perceived privacy risk on perceived ease of use is more pronounced (H18), consistent with Lallmahamood[144], who found that perceived privacy risk directly influences users' perception of technology ease of use. Essentially, when users encounter demands for sensitive information collection, their decision-making process becomes a dynamic trade-off between the costs of privacy disclosure and the benefits of technology adoption[145]. Specifically, privacy concerns not only consume cognitive resources for risk assessment but also impose a psychological burden, thereby raising the threshold for technology adoption[48]. To mitigate the negative cognitive impact of privacy risks, technology developers should assume the role of digital gatekeepers, focusing on preventing data misuse, algorithmic bias, and privacy infringement. By establishing algorithmic transparency mechanisms and data accountability frameworks, and embedding fairness verification procedures throughout the entire technology lifecycle, individuals can more accurately evaluate the operational logic and risk boundaries of the technology[146]. This trust-building approach, grounded in transparent governance, not only reduces users' perceived risk but also strengthens adoption confidence through verifiable ethical technology practices, ultimately achieving a balanced integration of privacy protection and technological effectiveness.

Finally, considering the unique characteristics of academic writing among fourth-year teacher education students, this study constructs a multivariable interaction model to reveal the underlying mechanisms influencing their adoption of LLMs. First, within the dimension of perceived risk, perceived privacy risk has a significant positive effect on perceived time risk (H16). This finding aligns with Prinsloo[147] perspective on the privacy paradox among digital natives: although teacher education students generally possess basic digital skills, concerns over privacy breaches lead to decision-making delays when using LLMs to process sensitive content in their theses (e.g., raw empirical data, interviewee information). Specifically, participants manually anonymized field research subjects, adjusted citation formats to prevent training data traceability, and even deliberately employed vague queries instead of precise prompts. Such "safety-first" coping strategies substantially reduce technological efficiency, further highlighting the critical role of privacy protection in optimizing technology use among teacher education students. Second, prior experience with academic writing technologies significantly predicts learning motivation (H5, H6). Successful engagement with digital writing tools, such as reference management software (e.g., Zotero) and grammar-checking applications (e.g., Grammarly), enhances teacher education students' "sense of control over intelligent technologies", thereby fostering a proactive attitude toward exploring the potential of LLMs for academic writing. This underscores the predictive role of prior experience in technology adoption.

Theoretical implications

This study extends and elaborates on the TAM to explore the behavioral intention of teacher education students in adopting LLMs for writing in the higher education context. By integrating external variables like learning motivation, perceived risk, self-efficacy, and usage experience, it refines the theoretical basis for understanding teacher education students' intentions to use LLMs for writing.

The interesting findings of this study still require further empirical evidence. Specifically, the study refines the subdimensions of learning motivation and perceived risk, and explores the interactions between subjective norms and goal achievement, as well as between perceived time risk and perceived privacy risk. This detailed analysis introduces new external variables into the TAM and provides theoretical support for related research.

Another theoretical contribution of this study is the unique attributes of LLMs in writing applications. Currently, research on LLMs is still in its early stages, and more studies are needed to better understand the willingness and influencing factors of teacher education students in using LLMs for writing.

Practical implications

First, the study indicates that subjective norms significantly influence teacher education students' intention to use LLMs for academic writing. Therefore, educators should fully consider the impact of sociocultural contexts on students' technology acceptance behavior. This can be achieved through two key strategies: (1) integrating an "LLM-assisted writing" module into writing courses, where instructors demonstrate standardized workflows for LLM-assisted literature reviews to reshape students' perceptions of technology; and (2) implementing a process-based evaluation system that categorizes the extent of LLM involvement (e.g., "LLM-assisted level" vs. "LLM-collaborative level") to guide appropriate usage.

Second, this study underscores the critical role of perceived ease of use in technology adoption. To be able to tailor to better fulfill the needs of teacher education students, LLM developers could enable a feature package or packages with such features as automatic generation of tables for coding text observations or annotated explanations of educational statistics formulas. Further, a "novice-to-expert" mode switch can be included to allow beginners to have structured writing templates for the start while providing advanced personalizations to expert users. Furthermore, such a localized deployment strategy must incorporate real-time data anonymization and come with a 48-h auto deletion system for writing content for the data to be safe.

Third, this has practical implications for policymakers, higher education institutions, and technology companies regarding the implementation of LLMs in academic writing within higher education. (1) It establishes educational technology policies that define the use of LLMs in academic writing. Such policies would forbid the use of LLMs in producing analysis conclusions based on data while allowing them to assist in the designing of research. (2) This is done by creating a conducive environment of collaboration amongst higher education institutions and technology companies. With this data trust mechanism in place, anonymized academic writing data including multi-version revision histories and cross-text citation linkages, among other things, could be securely shared supporting the production of discipline-specific ethical review modules. (3) This also encourages the implementation of intelligent writing workshops in universities to devise a "Human–Machine Collaborative Competency Framework" in these workshops. These courses should focus on three core skills: designing precise prompts based on research questions (e.g., translating complex methodologies into executable instructions), verifying the factual accuracy of machine-generated outputs (e.g., cross-validating data and chart logic), and integrating machine-generated knowledge with human expertise (e.g., transforming model-generated literature comparisons into research hypotheses). Finally, by implementing digital tracking of the writing process, institutions can dynamically assess the technological proficiency of both students and faculty, providing empirical evidence to support the ethical use of LLMs in academic contexts.

Limitations and future research

There are three main limitations in this research: First, the cross-sectional approach in this research restricts the ability to establish causal links. Future cohort studies are needed to confirm these findings and investigate how LLMs are used in teacher education students' writing over time. Second, the sample in this study is limited to fourth-year teacher education students from Chinese higher education institutions, so the external validity of the results is somewhat restricted. Future studies should apply the model in various contexts. Additionally, they should compare how different contextual factors impact teacher education students' intentions to adopt technology[148]. Finally, moderator variables are crucial for revealing the underlying mechanisms between independent and dependent variables. However, this study did not explore the moderating effects of demographic variables. Future research could include moderating variables, such as gender, discipline, and place of origin, to explore and extend the research model.

Conclusions

This study aims to examine the acceptance of LLMs for academic writing among fourth-year teacher education students in higher education. Based on the TAM, the research framework comprises ten constructs: self-efficacy (SE), experience (EX), subjective norms (SN), achievement of goals (AG), perceived time risk (PTR), perceived privacy risk (PPR), perceived usefulness (PU), perceived ease of use (PEOU), attitude toward use (ATU), and behavioral intention (BI). The findings reveal that fourth-year teacher education students exhibit a positive attitude toward adopting LLMs for academic writing. Path analysis indicates significant relationships among the constructs, with 21 out of 23 hypothesized pathways being supported. Notably, subjective norms emerged as a key predictor of behavioral intention to use LLMs for writing. Both perceived ease of use and perceived usefulness jointly influence attitudes toward use, with the former exerting a stronger effect. Surprisingly, perceived time risk does not significantly impact perceived ease of use but has a substantial negative effect on perceived usefulness. Meanwhile, perceived privacy risk strongly affects perceived ease of use but does not significantly influence perceived usefulness. Additionally, the study explores the underexamined interaction effects between perceived privacy risk and perceived time risk, shedding light on their combined influence on technology acceptance. In conclusion, this study provides new insights and empirical evidence on the acceptance of LLMs in higher education. Future research could extend the model by incorporating moderating variables to further elucidate the mechanisms underlying LLM adoption.

Data availability

This article does not provide data because it involves the user's personal privacy, if you have any special needs, please contact the First Author Yulin Gong.

Received: 1 February 2025; Accepted: 20 May 2025
Published online: 01 September 2025

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Acknowledgements

This research did not receive any specific grant from funding agencies in the public, commercial, or non-profit sectors.

Author contributions

Y.G. conceived and designed the experiments; performed the experiments; analyzed and interpreted the data; contributed analysis tools or data; wrote the paper; C.X. analyzed and interpreted the data;contributed analysis tools or data; S.L. analyzed and interpreted the data;contributed analysis tools or data;wrote the paper; J.L. analyzed and interpreted the data;contributed analysis tools or data;

Declarations

Competing interests

The authors declare no competing interests.

Ethical approval and informed consent

All methods were carried out in accordance with relevant guidelines and regulations. All experimental protocols were approved by the Academic Committee of the China Institute of Rural Education Development of Northeast Normal University. Informed consent was obtained from all subjects and/or their legal guardian(s).

Declare the use of generative AI and AI-assisted technologies in the writing process

In the preparation of this study, the authors did not use any generative AI or AI-assisted technologies.

Additional information

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