The Impacts of Students' Acceptance of ChatGPT on Their Academic Self-Efficacy in a Personalized Learning Environment

LE THI TRUC MAI*
TRAN VAN KHUE
English Language Department, FPT University, Vietnam
***Corresponding author email: mailtt15@fe.edu.vn**

Article information

Article history:
Received: 1 Feb 2024
Accepted: 14 Nov 2025
Available online: 25 Nov 2025

Keywords:
ChatGPT acceptance
Vietnamese higher education
Academic self-efficacy
Personalized learning
Technology Acceptance Model (TAM)

Abstract

Literature on educational technology has highlighted the roles of AI in personalizing students' learning and the relationship between learners' acceptance of technology use and their academic self-efficacy beliefs, both of which contribute to enhancing academic achievement. ChatGPT, a generative language model recently developed by OpenAI, offers opportunities and poses challenges for education. However, limited research has examined how students use ChatGPT to support their personalized learning and the impact of their acceptance of ChatGPT on students' academic self-efficacy. This study investigated Vietnamese undergraduates' use of ChatGPT for their personalized learning. It examined the effects of their acceptance of ChatGPT on their academic self-efficacy at a private university in Vietnam. Results from the surveys and interviews indicated that students used ChatGPT to explain and summarize information, answer questions, provide feedback, create texts, and write code. Furthermore, students' perceived usefulness of ChatGPT did not directly affect their academic self-efficacy. Instead, students' perceived ease of use and usefulness of ChatGPT indirectly affected students' academic self-efficacy through students' attitudes toward ChatGPT. These results suggest improving students' attitudes is critical for strengthening students' academic self-efficacy in ChatGPT-mediated learning. The study recommends providing structured guidance on using ChatGPT effectively and ethically, which aligns with Vietnam's 2025 framework of digital competence for learners.

INTRODUCTION

Chat Generative Pre-trained Transformer (GPT) is an artificial intelligence (AI) chatbot developed by OpenAI and launched in November 2022 (Liebrenz et al., 2023). Current research has confirmed these educational benefits of ChatGPT, such as providing information across various fields, offering timely feedback and generating ideas for writing (Ngo, 2023), as well as supporting students' personalized learning (Firat, 2023; Liu & Ma, 2023; Ngo, 2023). Anders

This paper was specially selected to be published from the FPT Conference of Language and Education (FCLE) that ran from 20 to 21 January 2024 at FPT University's Can Tho campus in Vietnam.

(2023) further proposed several ways that students can use ChatGPT to support their learning, including answering questions, summarizing and explaining information, creating texts, giving feedback, and writing code.

Despite these advantages, several concerns has been raised regarding reliable sources, the appropriate use of idiomatic expressions (Ngo, 2023), academic integrity (Firat, 2023), the potential disruption learning process (Rudolph et al., 2023) and even the dehumanization of AI (Chomsky et al., 2023; Rudolph et al., 2023). Nevertheless, ChatGPT has attracted considerable number of users (Menon & Shilpa, 2023). Although its adoption is widespread, policies and institutional guidelines for pedagogical use of generative AI (GenAI) remain limited. For example, An et al. (2025) found that 42% of 50 investigated universities in the United States had established guidelines for students, and only 12 universities recommended students check syllabi and consult their instructors before using such tools. Similarly, Evangelista (2025) conducted a systematic review of 76 articles and suggested the urgent need to have a guideline for ethical AI use, together with comprehensive training for both educators and students. These findings indicate that while GenAI tools such as ChatGPT have been widely implemented in education, the consistent guidelines and policies have not yet to be standardized.

In Vietnam, the Ministry of Education and Training (MOET) issued the Digital Competence Framework for Learners via Circular No. 02/2025/TT-BGDDT in January 2025. The framework emphasizes the integration of AI tools into learning activities, the responsible use and ability to evaluate AI-generated output (MOET, 2025). This initiative signals that Vietnam is moving forward structured and policy-driven guidance on AI in education.

Existing studies in the Vietnamese context have revealed diverse findings. Empirical studies on ChatGPT highlight students' positive attitudes toward the tool for their learning (Le & Tran, 2024; Ngo, 2023), their intention to use it in the future (Le & Tran, 2024), the tool's limitations (Vo & Nguyen, 2024), its impacts on students' performance (Tran & Duong, 2024) and students' purposes of using ChatGPT (Nguyen, 2024). However, research on students leveraging ChatGPT for personalized learning remains limited in Vietnam prior to the introduction of the 2025 Digital Competence Framework for Learners.

Zimmerman (2018) argued that successful personalized learning allows students to enhance their self-efficacy. Current experimental research on ChatGPT (e.g., R. Yilmaz & Yilmaz, 2023) and other types of chatbots (e.g., Lee et al., 2022) have indicated that chatbot technology can enhance students' academic self-efficacy, which refers to a learner's judgement about his or her ability to successfully accomplish academic goals (Bandura, 1997; Elias & MacDonald, 2007). Bouzar et al. (2024) explained that self-efficacy could be developed through automatic feedback and a sense of achievement gained from using ChatGPT. In line with this, prior research in educational technology has shown that the nature of the technological devices perceived by students could have impacts on their academic self-efficacy (Granić & Marangunić, 2019). Additionally, students' attitudes toward technology in learning also played a role in shaping their academic self-efficacy (Regatto-Bonifaz & Viteri-Miranda, 2023; Ünal et al., 2019). Likewise, perceived usefulness and attitude from the Technology Acceptance Model (TAM) have been found to have a relationship with students' confidence in their academic capabilities (e.g., Hanham et al., 2021; Regatto-Bonifaz & Viteri-Miranda, 2023). In the scope of this study, other external factors of extended TAM such as social influence and facilitating conditions, have not been examined. This is because at the time this research was conducted, there was limited or no clear guidance on the use of ChatGPT for learning. This lack of institutional direction might have constrained the ability of external factors to effectively support students in the use of the tool.

Therefore, this study focuses on the three core concepts of the original TAM, including perceived ease of use (PEU), perceived usefulness (PU), and attitudes toward technology (ATT), and their impacts on students' academic self-efficacy (ASE). This study aims to address the following questions:

1. In what ways did the participants use ChatGPT for personalized learning?
2. To what extent did the participants' acceptance of ChatGPT impact on their academic self-efficacy?

By addressing these questions, this study aims to help educators and policymakers understand students' ChatGPT-mediated learning practices as well as the impact of their ChatGPT acceptance on their academic self-efficacy. These insights would encourage them to develop effective strategies to integrate ChatGPT into educational settings for effective and responsible use, potentially enhancing students' learning experiences and outcomes.

LITERATURE REVIEW

Personalized learning and its benefits

Personalized learning, as defined by the United States National Education Technology Plan 2017 (cited in Xie et al., 2019), emphasizes tailoring the pace of learning and instructional approaches to meet the individual needs of each learner. In addition, it involves incorporating meaningful and relevant learning activities driven by the learners' interests and often initiated by the learners themselves. In other words, personalized learning involves creating learning experiences that accommodate individual learners' unique characteristics and preferences.

Personalized learning has been shown to benefit students' academic performance. Zhang et al. (2020) systematically identified and synthesized 71 empirical studies on implementing personalized learning between 2006 and 2019. The findings showed that personalized learning could improve students' learning outcomes and engagement toward learning, while some studies reported non-significant impacts on learning outcomes. Off the benefits, enhancing self-efficacy by personalized learning environment is also investigated by several studies. For example, Hall et al. (2019) conducted a mixed-method study involving 344 teachers engaged in personalized training of ICT integration in PreK-12 classrooms. They concluded that the personalized training program improved the teachers' self-efficacy in using technology in the classroom. Likewise, Guyah et al. (2021) used a quasi-experimental method with pretest and posttest control group design involving 143 chemistry students in Nigeria. The results revealed that students in the experimental group, who experienced personalized learning instructional strategies, demonstrated a higher level of self-efficacy.

The relationship between AI technology and personalized learning

AI technology has been considered a means to promote personalized learning environments. Xie et al. (2019) reviewed 70 articles from six Social Sciences Citation Index journals in educational technology from 2007 to 2017. They found that most of the studies on personalized learning focused on traditional computer devices, with only a few studies shedding light on the role of smart devices. In addition, they identified the rapid development of AI as a significant opportunity for personalized learning on smart devices. In the same vein, Li and Wong (2021) emphasized the significance of technology in personalization of learning by reviewing 203 Scopus-indexed journal papers published from 2001 to 2018. A more recent study conducted by Al-Badi and Khan (2022) on 91 learners and instructors at a higher education institution in Oman, using Independent-Samples Mann-Whitney U Test and Independent-Krushkal-Wallis Test. The results revealed that these participants had positive attitudes toward AI in personalized learning. The authors explained that the algorithms analyzed data collected from individual learners' assessments, interactions, and learning behaviors to provide personalized content, activities, feedback, and ongoing assessments based on their needs.

Likewise, Pratama et al. (2023) conducted a qualitative descriptive method with a triangulated approach by utilizing questionnaires, interviews, observations and document analysis to collect data from 29 educational technology students at Indonesian Christian University of Toraja. They found that AI could serve as a virtual tutor to provide personal guidance for learners with lower proficiency levels outside the classroom. Its ability to give supplementary materials, exercises, and proper feedback helped learners deepen their insight into a specific topic. Therefore, students could use the system to answer their questions, explain something they need, and have a wide range of resources. In general, AI technology can optimize personalized learning in ways that are difficult for educators to achieve due to their inherent limitations such as time constraints and limited availability (Limo et al., 2023; van der Vorst & Jelicic, 2019).

ChatGPT, as an AI tool trained on vast amounts of data, can effectively address students' needs for personalized learning by understanding the context of conversations (Limo et al., 2023). Focusing on personalized learning, Atlas (2023), in his online book, highlights three ways ChatGPT can support students, including providing feedback on their performance, delivering materials tailored to their interests and preferences, and offering instruction adapted to their unique learning styles. In this regard, learning with ChatGPT as a tutor allows students to progress at their own pace (Su & Yang, 2023), thereby facilitating successful personalized learning (Agbong-Coates, 2024).

A recent study conducted by Limo et al. (2023) involving 287 undergraduate and graduate students at the University of Lima revealed that 68.8 percent of participants reported using ChatGPT for personalized learning. The study also found that ChatGPT encouraged students to take greater responsibility for their learning by asking questions, receiving personal responses, and accessing additional materials. However, personalizing learning with ChatGPT also presents challenges, including concerns about privacy and bias (Ayeni et al., 2024), negative impacts on students' critical thinking (Ibrahim et al., 2023), incorrect responses (Xu et al., 2024), and the loss of human interaction (Bauer et al., 2018; Sana et al., 2013; Xu et al., 2024).

Despite these challenges, ChatGPT is considered a game changer in personalizing learning and has been widely used by Vietnamese students since its emergence. Research on ChatGPT in the Vietnamese context has primarily focused on students' perceptions of its advantages and disadvantages (Ngo, 2023; Pham & Le, 2024), factors influencing students' intention to use ChatGPT (Le & Tran, 2024; Vo & Nguyen, 2024), and the impacts of ChatGPT on students' performance (Tran & Duong, 2024) and students' use of ChatGPT for both academic and other work-related purposes (Nguyen, 2024). However, there is limited research shedding light on the specific functions of ChatGPT utilized by students to support their learning in the current context. Addressing this gap, the present study aims to understand how Vietnamese students engage with ChatGPT's affordances, particularly the functions they employ to support their learning.

Technology acceptance constructs

This study adopts the original Technology Acceptance Model (TAM), focusing on its core constructs, perceived usefulness (PU), perceived ease of use (PEU), and attitudes toward technology (ATT) to examine the impact of students' ChatGPT acceptance on their academic self-efficacy (ASE) in personalized learning. External factors such as social influence and facilitating conditions were excluded because the use of ChatGPT in this context was largely self-initiated and unguided, with no institutional or instructional guidance. Building on this framework, the study defined PU, PEU, and ATT following the Technology Acceptance Model (Davis, 1989). PU refers to the belief that using a particular technology will improve user's efficiency and effectiveness (Davis, 1989). PEU pertains to users' opinions regarding how much effort will be needed to learn and operate a specific technology (Davis, 1989). In the TAM framework, PEU influences PU, meaning that if users find the technology easy to use, they are more likely to perceive it as useful. Both PU and PEU subsequently influence ATT towards using the technology, the third construct in the original model. These constructs are internal factors that shape how students perceive technology (Scherer & Teo, 2019) and influence their intention to use it.

Initially, the key factors PU and PEU were considered to be directly influenced by the characteristics of the system (Granić & Marangunić, 2019). Over time, numerous external factors have been identified, leading to the extensions of the TAM, such as TAM2 and TAM3. These models introduced social and organizational variables (e.g., subjective norms, experience, and facilitating conditions) that affect technology adoption. Although external factors play a significant role in shaping students' acceptance of technology, they primarily have indirect effects by influencing either PEU or PU within the model. Another extension of TAM is the Unified Theory of Acceptance and Use of Technology (UTAUT). According to this model, social influence (e.g., peers, and teachers), facilitating conditions for effective use of new technology described as external conditions (Venkatesh et al., 2003), together with effort expectancy and performance expectancy, which correspond to PU and PE in earlier versions of TAM, influence users' behavioral intension and use behavior. In the current research, external factors such as social influences and facilitating conditions have not been explored because the use of ChatGPT in the context can be considered as self-initiated and unguided. Therefore, these external influences might not be qualified enough for providing effective support for efficient ChatGPT use. Therefore, this study exclusively focused on the internal factors from the original TAM model, referred to as "validity and simplicity" (Yang et al., 2024, p. 6), which aligns with several current research studies on ChatGPT acceptance in Vietnam and the world (e.g., Le & Tran, 2024; Liu & Ma, 2023; Vo & Nguyen, 2024; Zou & Huang, 2023).

Academic self-efficacy

Academic self-efficacy (ASE) refers to an individual's judgment of his or her ability to accomplish a desired outcome, such as achieving educational goals (Bandura, 1997; Elias & MacDonald, 2007). Research suggests that students with high self-efficacy are often more motivated to take action since they tend to put greater effort and show determination in solving tasks, usually opting for more challenging ones (Hanham et al., 2021). Besides, numerous studies have established a significant relationship between self-efficacy beliefs and academic achievement (Meng & Zhang, 2023; Talsma et al., 2018; Travis et al., 2020; Yokoyama, 2019). These findings indicate that students' confidence in their capacities significantly affect their academic success. In other words, students with a higher sense of self-efficacy tend to learn more confidently and solve academic tasks more effectively, thereby improving their academic performance. Therefore, gaining insight into ASE is crucial, as students' perception of their self-efficacy in completing a task can foster their active engagement with the task, eventually shaping their ability to attain desired outcomes (Bandura, 1997).

The relationship between AI chatbots and students' ASE

Parsakia (2023) indicated that ChatGPT significantly affects academic self-efficacy due to its ability to provide immediate feedback, facilitate personalized learning, and enhance a sense of achievement and competence. Current research has highlighted the significant role of AI chatbots in promoting students' learning self-efficacy. Particularly, Lee et al. (2022) conducted a quasi-experimental study on 20 students in a control group and 18 students in an experimental group at a university in Taiwan. The latter group used AI based chatbots for post-class reviews in public health courses. Comparing the data from the two groups, they found that using AI-based chatbots improved students' self-efficacy. Similarly, Chang et al. (2022) carried out the study with a quasi-experimental design with two groups of 36 university nursing students from northern Taiwan and found that the students' self-efficacy in the experimental group, which employed the mobile chatbot for their learning, demonstrated significant improvements in self-efficacy. These results align with Yilmaz et al. (2023), who investigated 45 undergraduate students in a programming course, using an experimental design. The findings indicated that ChatGPT enhanced students' programming self-efficacy by supporting the coding process. However, due to its natural limitation of small sample size and the five-week duration, its findings require further investigation in different contexts to confirm generalizability. In the same vein, Urban et al. (2024) examined two groups, including one group with 77 university students using ChatGPT to complete tasks and another group of 68 students who worked without it. They found that ChatGPT significantly improved students' self-efficacy in task-solving.

While most of these studies demonstrate the positive influence of AI chatbots on students' self-efficacy, other evidence suggests that satisfaction with chatbot use may be a more decisive factor for enhancing academic self-efficacy than frequency of use. In a quantitative cross-sectional correlation study, Yildiz-Durak (2023) examined 86 university in Turkey who used a chatbot created through the Flow XO environment, a platform that enables the creation of conversational agents that support user engagement and communication across multiple digital and social platforms. The chatbot was primarily used to study visual design and hexadecimal color codes. Based on the questionnaire developed through a conceptual framework, the study found that students satisfied with chatbot usage tended to have higher visual design self-efficacy. However, the frequency of chatbot use alone did not enhance self-efficacy. This finding implies that students' emotional engagement with chatbot tools may be more critical for building academic self-efficacy than merely exposure. It also highlights the importance of learners' positive attitudes and meaningful interaction with AI tools.

The relationships among the constructs PEU, PU, ATT and ASE

The relationships among the constructs PEU, PU, and ATT have been well established through TAM proposed by Davis (1989). When a technology is easy to use, it enables students to perceive its usefulness more effectively. Both PU and PEU directly influence users' attitudes. The easier and more useful the technology is, the more positive attitudes students are likely to develop toward it. This relationship was confirmed by Le and Tran (2024), who identified these constructs as influential factors of behavioral intention. Similarly, Liu and Ma (2023) conducted a cross-sectional study with 405 EFL learners and validated the TAM model. The findings showed that PEU positively and significantly influenced PU, and PU directly affected students' ATT. In addition, PEU indirectly influenced students' ATT, a finding also supported by Tiwari et al. (2024), who investigated factors influencing students' use of ChatGPT. Interestingly, this finding contrasts with the original TAM model developed by Davis (1989), which indicated a direct effect of PEU on ATT. Based on this divergence, we hypothesized that:

(1) Students' PEU of ChatGPT affects their PU.
(2) Students' PEU of ChatGPT affects their ATT.
(3) Students' PU of ChatGPT affects their ATT.

Furthermore, previous research on technology acceptance has also shown a relationship between PU and students' ASE. Particularly, Hanham et al. (2021) carried out a study with 365 undergraduate students from a university in Australia using CFA and SEM methods, and found that the PU of technology affected ASE through online tutoring. This result occurs because students not only gained a better understanding of concepts and fulfilled assignments but also received constructive feedback, which is considered vital for improving self-efficacy (Chan & Lam, 2010, cited in Hanham et al., 2021). Similarly, ChatGPT offers numerous functions to support learning, such as answering questions, explaining and summarizing information, and providing students with timely feedback. Therefore, based on these findings, we hypothesized that:

(4) Students' PU of ChatGPT influences their ASE.

The TAM model suggested that individuals' beliefs, including PEU and PU, influence their ATT towards technology and behavioral intention to use it. Based on this model, ATT serves as a mediator between beliefs and actions. In the educational context, this implies that students' positive ATT can increase their engagement in learning activities, promote deeper understanding and facilitate task completion, which in turn enhances their ASE. Research has also demonstrated the correlation between students' ATT and their ASE, which means that a positive attitude would enhance academic self-efficacy and vice versa. For example, Ünal et al. (2019) used correlation analysis to examined the relationship between students' attitudes towards ICT and their ASE among 249 Anatolian high school students in Istanbul across different grades. They found that students with positive attitudes toward ICT and media tools tend to have higher ASE and vice versa. Likewise, Regatto-Bonifaz and Viteri-Miranda (2023) conducted a non-experimental design of descriptive and cross sectional study with 570 students (76% female, 24% male; mean age = 25.29), and found a significant correlation between students' ASE and ATT. In the context of ChatGPT, students with positive attitudes toward using this educational tool are more likely to employ it to support their learning, complete their assignments, and improve their understanding, which can, in turn, enhance their ASE. Therefore, the following hypothesis was proposed:

(5) Students' ATT toward ChatGPT affects their ASE.

From the previous studies, there is scant research exploring how the constructs PEU, PU, and ATT from TAM model effect on student's ASE when using ChatGPT for their learning. Therefore, our current research aims to bridge the gaps by examining these relationships in the Vietnamese higher education context.

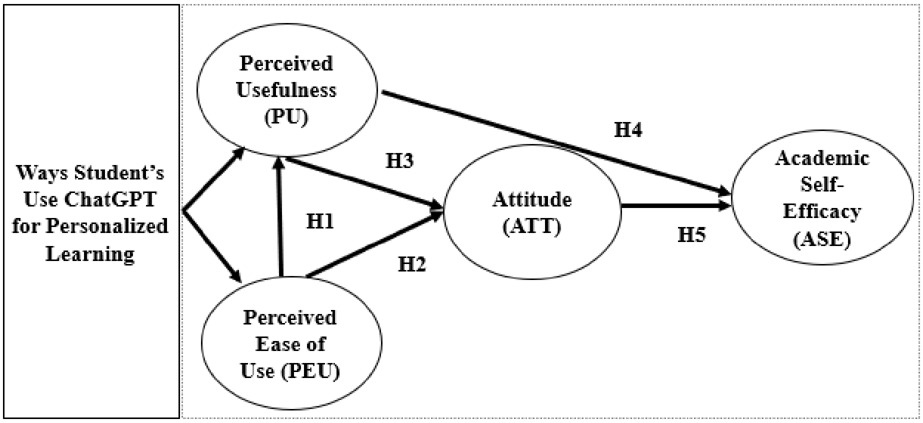

Figure 1 Research model (Adapted from TAM Model by Davis, 1989)

METHODOLOGY

Research method

In this study, the researchers applied two distinct research designs, each addressing a specific research question. To answer the first research question, a mixed-methods design was employed. Specifically, quantitative data on how students utilized ChatGPT for personalized learning were collected through a survey, while qualitative data providing further explanations of their usage were gathered through follow-up interviews. This approach enabled the collection of both quantitative and qualitative data, thereby reducing bias and subjectivity in the analysis (Creswell, 2009).

To answer the second research question, a quantitative design was adopted to test the hypotheses concerning the effects of students' acceptance of ChatGPT on their academic self-efficacy. This method was appropriate for testing theories or explanations, as recommended by Creswell and Creswell (2018), and was therefore considered suitable for addressing our research aim.

Participants

Among the 298 responses obtained from the questionnaire, 263 responses (88%) were qualified for data analysis. A total of 263 participants, including 135 females and 128 males, from a private university in the Mekong Delta participated in this study. They were between 18 and 22 years old and came from different departments. The participants were recruited through a convenience sampling technique. They were approached on campus or in their classrooms, where the researchers presented the purpose of the study and invited them to complete the questionnaire.

For the qualitative phrase, participants were randomly invited to interviews via Google Meet based on their responses to the final item of the questionnaire, which they were asked if they were willing to participate in a follow-up interview. This random selection ensured a diverse representation of perspectives. Ten participants were ultimately selected for interviews, following Lincoln et al.'s (1985) recommendation that sampling should continue until no new information is obtained, which is referred to as saturation in qualitative research.

After conducting interviews with the first ten participants, their responses were becoming increasingly similar, suggesting that we had reached a point of redundancy. As a result, we decided to stop at ten participants, as this number provided sufficient data to answer the research questions. This decision is also supported by empirical evidence by Guest et al. (2006) who indicated that cored themes appear in the sixth interviews and Hennink and Kaiser's (2022) systematic review revealed the acceptable range for saturation from 9 to 17 interviewees. There were no specific characteristics required for participation. Still, the researchers aimed for a balanced selection of demographics (e.g., gender, age, academic background) to capture a broad range of experiences with ChatGPT in personalized learning. Before completing the questionnaire or partaking in the interview, the participants had to sign consent forms. To protect participants' anonymity, each was assigned a pseudonym during the interview process. The codenames under alphanumerical forms were assigned to each participant, following the guidelines by Heaton (2022). Although the researchers had previously taught a small number of first-year students, the semester had ended by the time the study was conducted, and they no longer held any direct authority or power over the participants. This process ensured that the participants could freely and voluntarily share their experiences without concern about any influence or pressure from us. At the time of the study, the participants had been using ChatGPT for at least three months. Table 1 presents detailed demographic information about the participants.

Table 1
Participant demographics

		N	Percentage (%)
Gender	Male	128	48.7
	Female	135	51.3
Age	18–22	263	100
Study discipline	Digital marketing	34	12.9
	Information technology	87	33.1
	Multimedia communication	16	6.1
	Languages	57	21.7
	Business administration	49	18.6
	Graphic design	20	7.6
Years of study	Year 1	30	11.4
	Year 2	107	40.7
	Year 3	76	28.9
	Year 4	50	19

Research instruments

The research instruments included a survey questionnaire and semi-structured interviews. The first section of the questionnaire gathered participants' demographic information, while the second section contained items aimed at addressing the two research questions.

Regarding the first research question, the questionnaire and semi-structured interviews were used to examine how participants used ChatGPT to support their personalized learning. This section included six items of the participants' usage of ChatGPT (UChat). The researchers developed these questions based on the distinctive capacity of ChatGPT identified by Anders (2023). The items were rated on a six-point scale, a positively packed rating scale (Lam & Klockars, 1982), consisting of two negative choices (e.g., strongly disagree and mostly disagree) and four positive choices (slightly agree, moderately agree, mostly agree, and strongly agree). The researchers applied the positively packed structure because prior researchers (e.g., Brown, 2004; Lam & Klockars, 1982) demonstrated that such scale generated greater variance in responses, making the data more informative and improving discrimination among participants' responses. Besides the questionnaire, two open-ended questions were used to further investigate how the participants use ChatGPT to support their personalized learning and their reasons for using it. These questions included (1) What did you use ChatGPT for in your learning? (2) Why did you use ChatGPT for this?

In terms of the second research question, twelve items using the six-point scale from the validated questionnaires developed by Liu and Ma (2023) were adapted to measure constructs related to the TAM model, including PEU (4 items), PU (4 items), and ATT (4 items) (see Appendix 1). Apart from the 12 items, the five-item ASE from the Patterns of Adaptive Learning Scales developed by Midgley et al. (2000) were also adapted. These items have been proved to be effective in research related to university students (Elliot et al., 2011). The items were rated using a five-point ordinal scale. The participants rated the items based on their perceived truthfulness, with response options, including one (not at all true), two (slightly true), three (moderately true), four (mostly true), and five (very true) (see Appendix 2). The researchers translated the questionnaire independently and then compared the translated versions. In cases of discrepancies, they discussed until reaching an agreement on the final version.

Data collection and analysis

An online questionnaire was sent to the participants via Google Forms. Prior to its administration, a pilot test with 45 students was conducted to examine the reliability of the questionnaire. The Cronbach's alpha coefficients for all variables exceeded 0.6 and the correlated item–total correlations were over 0.3, indicating that the questionnaire was qualified to collect the data (Cresswell & Creswell, 2018). The Cronbach's alphas of the variables are presented in Table 2.

Table 2
The Cronbach's Alpha of each construct

Constructs	Cronbach's Alpha	N of items
PEU	.916	4
PU	.943	4
ATT	.922	4
ASE	.874	5
UChat	.843	6

For the quantitative data, SPSS version 25 was utilized to run descriptive data analysis to examine the respondents' use of ChatGPT to support their learning. Additionally, the researchers employed the partial-least squares method of structural equation modeling using SmartPLS Version 4.9.0.5 to examine the effects of the Technology Acceptance Model constructs on ASE.

For the qualitative data, interviews were conducted via Google Meet at times and places convenient for the participants. This approach ensured that they were in comfortable settings, allowing them to share their experiences more freely, which helped us gather fruitful data. The interview lasted about 15 minutes to respect participants' time and avoid interview fatigue, which can sometimes affect the quality of responses in longer sessions. Keeping the interview brief ensured participants could provide thoughtful and clear answers without feeling overwhelmed. Vietnamese, the participants' mother tongue, was used during the interviews to ensure that students were at ease to share their experience.

For the qualitative data analysis, a deductive thematic analysis following the six steps suggested by Braun and Clarke (2023) was employed to code the open-ended responses manually. Their guidance was used to ensure that the analysis was careful, organized, and trustworthy. The coding process began by transcribing all interviews and reading them several times to get familiar with what participants said. Then, Anders' (2023) six functional uses of ChatGPT, including explaining information, summarizing content, answering questions, receiving feedback, generating content, and writing code were adopted as the coding categories. While reading, useful phrases like "explain" or "clarify" were highlighted and assigned to the appropriate category. For example, one student said, "Whenever I was not quite sure to understand the lessons taught in my class, I got ChatGPT to explain it for me because I felt shy to ask my lecturers." The researchers placed this under explaining information. After finishing coding, they grouped similar responses under each category and checked the transcripts again to ensure the themes accurately represented the data.

Several strategies to ensure the reliability of the qualitative data were applied. Firstly, the researchers employed inter-rater reliability to enhance the coding process. Each of the researchers coded the interview transcripts independently and compared the coding results together. Any discrepancies were reviewed and discussed until reaching agreement. This process helped minimize bias and strengthen the credibility of the findings. Secondly, the translated versions of the results were proofread by a colleague with over five years of experience in teaching translation courses to ensure accuracy and consistency.

RESULTS

Students' usage of ChatGPT for their personalized learning

Table 3
The participants' usage of ChatGPT for their personalized learning

Students' use of ChatGPT (N = 263)	Mean	SD
I use ChatGPT to explain information.	4.94	.947
I use ChatGPT to summarize information.	4.82	1.054
I use ChatGPT to answer questions.	4.68	1.066
I use ChatGPT to provide feedback on my assignments.	4.46	1.312
I use ChatGPT to create texts.	4.45	1.231
I use ChatGPT to write codes.	3.78	1.710

As seen in Table 3, the participants employed the various functions of ChatGPT for their personalized learning. The most common usage of ChatGPT was elaborating information (M = 4.94; SD = .947). The participants reported that they used ChatGPT to elaborate concepts from the coursebooks that they found it difficult to understand, translate terminological terms, or seek an explanation for the codes demonstrated by their lecturers. Particularly, they claimed that

> *Whenever I was not quite sure to understand the lessons taught in my class, I got ChatGPT to explain for me because I felt shy to ask my lecturers.* ID9
>
> *When I had homework, but I did not know how to deal with it, I asked ChatGPT to do it and explained the results for me.* ID6

> *When I did not understand the course books, I used ChatGPT immediately. It helped me explain the technical terms and summarize the content. For example, when studying the functions of small items of laptops or computers, it was hard for me to understand by reading books. In such case, I copied the content and pasted it on ChatGPT platform for its explanation.* ID10

> *When I found it hard to understand lecturing slides or terms in the coursebooks that are so abstract for me to understand. I had ChatGPT explain and provide examples.* ID3

Summarizing information was rated as the second popular usage (M = 4.82; SD = 1.054). For example, participant ID2 reported that

> *I used it to respond to constructive questions on EN, an e-e-learning platform. I uploaded them and got Chat to provide answers [….] Then, I asked ChatGPT to condense the answers.*

Apart from summarising information, the participants stated that they used ChatGPT to answer questions (M = 4.68; SD = 1.066). Students enjoyed using this tool for answering questions. For them, the answers of ChatGPT were sometimes relevant but sometimes were not good. To use this effectively, they focused on testing the quality of the answers. For example,

> *ChatGPT was like an encyclopedia that could answer almost every question for me. It could provide the best answer. But to use it optimally for learning, I should also refer to other sources because there was a possibility that its answers sometimes were incorrect or outdated.* ID5

> *When my lecturer posed a question that I could not address it, or when I searched on Google and still could not find the answer, I turned to ChatGPT. For example, I was studying a probability and statistics course, and when the teacher assigned homework that I felt unable to do, I copied lecturer's question and pasted it into ChatGPT to seek answers. Once ChatGPT provided a solution, I was aware that it might be incorrect, normally, there might be errors in the data, so I tested it again by using the formulas from ChatGPT and a calculator with the given numbers.* ID10

Furthermore, ChatGPT served as a useful feedback provider for participants (M = 4.46; SD = 1.312). It could locate the mistakes, explain the weaknesses, and suggest ways to improve the work. It could even fix the errors to enhance product quality. These functions were addressed by the participants as follows,

> *When programming, if I made errors in some code, but I could not find the reasons, I would copy that code and asked ChatGPT to point out the mistakes. It could explain why they were wrong and how to improve them. It helped me identify the specific areas of the code that were not incorrect. When I still did not understand the mistakes, I asked for elaborations or asked it to correct the errors.* ID1

ChatGPT could help restructure the code for better clarity. In my field of expertise, it assisted me in finding coding errors, for example, if I forget a dot or made mistakes in a variable name. If the code was lengthy and I asked where something was, it immediately located it, or it could be an excellent tool to optimize the code. For instance, if the code ran slowly, ChatGPT could help optimize it. ID2

Additionally, participants reported they employed ChatGPT to generate various types of content, such as brainstorming ideas, creating outlines, and designing additional practice tasks (M = 4.45; SD = 1.231). They said that

I used ChatGPT to brainstorm ideas for my English writing task. When I had a writing task, I asked ChatGPT to provide some ideas. For example, my writing topic was about the advantages and disadvantages of learning a new language. I asked ChatGPT, and it provided me with lists of ideas about the topic. ID2

When I had assignments, such as a presentation, I asked ChatGPT to create an outline with main ideas for my presentation. ID4

I had ChatGPT write exercises or examples that were similar to my lessons so that I could do extra practice to consolidate my knowledge. ID7

Finally, using ChatGPT to write code was rated as the least common (M = 3.78; SD = 1.710). In the interviews, one student commented that he employed ChatGPT to write codes for assignments he did not understand well, so ChatGPT could generate a code framework. Then he could improve the quality of the code written by ChatGPT. He explained as follows

I was learning programming, so I often asked ChatGPT about code. When I did not understand some assignments well, I sent them to Chat. It generated a code framework for the given task. Starting from the provided framework, I then built a complete program and submitted it to the lecturer. ID6

To conclude, participants employed ChatGPT function to accommodate their personal learning needs. The next section presents the result of the second question.

The effects of students' ChatGPT acceptance on their academic self-efficacy

Instrument reliability and validity

Table 4

Measurement model parameter estimation

Constructs	Items	Factor loading	Cronbach's Alpha	Composite reliability	AVE
PEU	PEU1	0.835	0.860	0.905	0.704
	PEU2	0.833			
	PEU3	0.858			
	PEU4	0.829			

Constructs	Items	Factor loading	Cronbach's Alpha	Composite reliability	AVE
PU	PU1	0.881	0.902	0.931	0.772
	PU2	0.852			
	PU3	0.897			
	PU4	0.885			
ATT	ATT1	0.864	0.897	0.928	0.763
	ATT2	0.886			
	ATT3	0.877			
	ATT4	0.868			
ASE	ASE1	0.808	0.884	0.915	0.683
	ASE2	0.808			
	ASE3	0.872			
	ASE4	0.818			
	ASE5	0.825			

Table 4 indicated that factor loadings for the items in the measurement model were higher than the accepted threshold of 0.708 (Hair et al., 2018). Additionally, Cronbach's alpha and composite reliability were greater than 0.7 (Hair et al. 2018), indicating that these variables are internally reliable. Furthermore, the composite reliability and AVE were above 0.5, which showed that these variables were considered adequate. In addition, Table 5 showed that the Heterotrait-monotrait ratios (HTMT) were under 0.9 (Henseler et al., 2015). This means that the constructs' discriminant validity was acceptable.

Table 5

Heterotrait–monotrait ratio of correlations

Constructs	ASE	ATT	PEU	PU
ASE				
ATT	0.585	0.709		
PEU	0.458	0.843	0.711	
PU	0.516			

Collinearity analysis: to prevent problems related to collinearity, the variance inflation factor (VIF) should be less than 3 (Hair et al., 2018). As shown in Table 6, the constructs' VIFs were below the threshold value of 3, suggesting that the collinearity of the indicators did not occur.

Table 6

Evaluating collinearity of scale and model fit

	ASE	ATT	PEU	PU
ASE				
ATT	2.369			
PEU		1.673		1.000
PU	2.369	1.673		

Hypothesis testing

Table 7 and Figure 3 indicate that PEU ($\beta = 0.634$, $p = 0.000$) directly affected PU, which supported H1. Additionally, PEU ($\beta = 0.248$, $p = 0.000$) directly affected ATT, supporting H2. PU ($\beta = 0.603$, $p = 0.000$) directly influenced ATT, supporting H3. ATT ($\beta = 0.413$, $p = 0.000$) had a direct effect on ASE, supporting H4, while PU ($\beta = 0.147$, $p = 0.129 > 0.05$) showed no statistically significant direct impact on ASE, leading to the rejection of H5.

Table 7

Hypothesis testing results

Hypothesis	Relationships	Path coefficients	P-value	Results
H1	PEU -> PU	0.634	0.000	Supported
H2	PEU -> ATT	0.248	0.000	Supported
H3	PU -> ATT	0.603	0.000	Supported
H4	PU -> ASE	0.147	0.129	Rejected
H5	ATT -> ASE	0.413	0.000	Supported

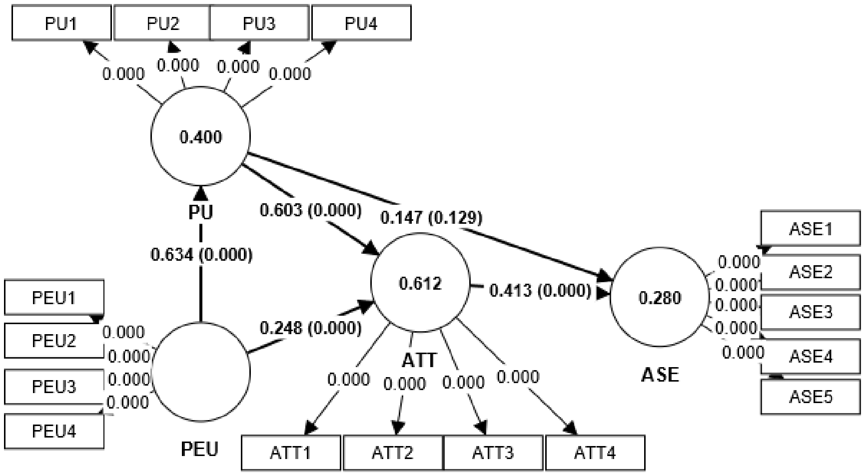

Figure 2 The results of the path coefficients

Results of the mediating effects of PU and ATT

The bootstrapping analysis was run to examine the mediating effects of PU and ATT. As shown in Table 8, the mediating effect of ATT on the relationship between PU and ATT was statistically significant ($\beta = 0.249$, $p = 0.000$). Similarly, the mediating effect of PU on the relationship of PEU and ATT was found to be statistically significant ($\beta = 0.383$, $p = 0.000$). In the same vein, ATT played a significant mediating in the relationship of PEU and ASE ($\beta = 0.102$, $p = 0.006$). In addition, PU and ATT also demonstrated significant mediating effects on the relationship of PEU and ASE ($\beta = 0.158$, $p = 0.000$), confirming the mediating role of PU and ATT in the impact of PEU and ASE. In contrast, the mediating effect of PU on the relationship of PEU and ASE was found to be not significant ($\beta = 0.093$, $p = 0.140$).

Table 8

The mediating effects of PU and ATT

Relationships	Path coefficients	P-value	Results
PU -> ATT -> ASE	0.249	0.000	Supported
PEU -> PU -> ATT	0.383	0.000	Supported
PEU -> ATT -> ASE	0.102	0.006	Supported
PEU -> PU -> ASE	0.093	0.140	Rejected
PEU -> PU -> ATT -> ASE	0.158	0.000	Supported

DISCUSSION

The present research aimed to explore how the participants utilized ChatGPT to personalize their learning and to examine whether their acceptance of ChatGPT influenced their ASE.

The findings revealed the versatile functions of ChatGPT, aligning with those reported by Nguyen (2024), who highlighted its use for summarizing information, generating ideas, language learning, and giving feedback. However, our results further showed that Vietnamese students also used ChatGPT for writing code which is supported by previous scholars (Anders, 2023; Limo et al., 2023; Xu et al., 2024). The difference may stem from the participants' academic majors. Such results highlight the diverse features ChatGPT that cater to various academic needs and emphasize its appeal as an educational tool, as noted by Menon and Shilpa (2023).

The TAM model was employed to examine how students' acceptance of ChatGPT affects their ASE. Four out of five hypotheses were confirmed. Specifically, the results indicated that PEU directly affected PU and indirectly affected ATT through PU, which supported the first three hypotheses. Additionally, ATT was found to directly affect students' ASE, supporting the fifth hypothesis. However, PU showed no direct effect on ASE, which led to the rejection of the fourth hypothesis.

The study's results reaffirm the relationship among the three TAM constructs, including PEU, PU, and ATT. Students who perceived ChatGPT as easy to use were more likely to find it helpful. Additionally, if PEU and PU were positively perceived, students were more likely to develop favorable attitudes toward using ChatGPT for learning. The findings are also consistent with the prior study by Le and Tran (2024), which identified PU and PEU as predictors of ATT. However, unlike the study that focused on behavioral intention, this study shed light on the relationship between the factors and ASE, offering broader implications for technological acceptance in education.

In this study, the proposed hypothesis (H2), concerning the relationship between PEU and ATT, was found to be different from the study by Liu and Ma (2023). According to the original TAM model (Davis, 1989), this contradiction can be explained by the characteristics of students aged 18–24 who used ChatGPT independently, without formal guidance. This group likely placed high value on PEU, as their ability to adapt to the tool and its user-friendly interface enabled them to navigate academic tasks, which positively shaped their attitudes and engagement. In contrast, Liu and Ma (2023) and Tiwari et al. (2024) investigated more diverse participant groups, with university students comprising only 24% and 66.67% of their samples, respectively. For these groups, PU appeared to be more significant. Their participants were more likely to use the tool to achieve benefits that were otherwise unattainable with other technologies, even if the tools had less user-friendly features, as noted by Tiwari et al. (2024). Another reason for this discrepancy might lie in participants' different experiences with the tool. Tiwari et al.'s (2024) participants, after watching several ChatGPT video tutorials, perceived ChatGPT to be difficult to use due to its unclear and confusing information, thereby weakening the direct relationship between PEU and ATT. In contrast, participants in this study were enthusiastic about the positive role of the tool, despite acknowledging its weaknesses. This is because the participants from the current study had employed the tools for their learning activities.

The results also established the direct effect of ATT on ASE in the context of ChatGPT use. Previous studies on educational technology, such as Regatto-Bonifaz and Viteri-Miranda (2023) and Ünal et al. (2019), primarily indicated a correlation between these two constructs. In contrast, this study demonstrates a causal relationship between them. Moreover, the direct effect of ATT on ASE aligns with Yildiz-Durak (2023), who highlighted the impact of students' satisfaction on their ASE in the context of a different chatbot. As an inherently positive emotional response, satisfaction closely aligns with positive ATT, as both represent pleasant sentiments toward a specific subject or experience. The results of this study indicate that ATT is a predictor of students' ASE. This means that if students have positive attitudes towards learning with ChatGPT, they are more likely to have higher levels of learning self-efficacy. Together with the previous study, the current research emphasizes the significant role of the psychological aspects of a technology-mediated learning environment.

Regarding the effect of PU on ASE, the findings contrast with Hanham et al. (2021), who reported a direct relationship between the two constructs in online learning. In this study, however, PU influenced ASE indirectly through ATT. Although students perceived ChatGPT as useful, this perception did not necessarily translate into higher ASE. The discrepancy might be explained by the nature of the tasks. This study revealed that students tended to rely on ChatGPT primarily to complete their assignments rather than to develop their skills, which may not be sufficient to build their ASE. In addition, the possibility of using GenAI output without thinking carefully may inhibit the learning process (Rudolph et al., 2023), another reason for hindering students' perceived ASE. In contrast, Hanham et al. (2021) examined online tutoring services where PU directly impacts self-efficacy through guided feedback and structured learning pathways. Personalizing learning with ChatGPT in the current context might lack such structured elements, contributing to the different findings.

This finding highlights merely recognizing ChatGPT as useful will not enhance self-efficacy unless it also fosters a positive attitude that drives repeated and reflective use. This is in line with earlier studies by Chang et al. (2022), Lee et al. (2022), Urban et al. (2024) and Yilmaz et al. (2023), which examined other types of chatbots using experimental research designs. Despite the differences in chatbot types and methodologies, the results across the studies converse, strengthening the credibility and generalizability of the findings of this study. The consistent pattern suggests that a positive ATT toward chatbots corresponds with improved ASE among students. However, the absence of structured, guided use in this study context may have limited opportunities for mastery experiences, the most influential sources of self-efficacy (Bandura, 1997); thereby, constraining more robust self-efficacy development. This contrasts with the findings of Hanham et al. (2021), where guided feedback and structured online tutoring environments led to stronger efficacy outcomes.

Beyond the TAM framework, these findings can also be contextualized within the 2025 Digital Competence Framework for Learners. These competencies identified by the 2025 framework can address challenges observed in the study, such as student's overreliance on ChatGPT without sufficient critical engagement. If it is well implemented, the framework could encourage more critical uses of AI tools, which could strengthen ASE in the Vietnamese higher education context. The findings of this study emphasize not only psychological aspects of technology mediated learning but also the importance of aligning students' practices with Vietnam's national digital transformation initiatives.

IMPLICATIONS

Practical implications

Several recommendations can be made to strengthen Vietnamese students' attitudes toward GenAI tools like ChatGPT and enhance their academic self-efficacy. First, educators should integrate AI literacy training, based on the 2025 Digital Competence Framework for Learners, into academic courses to enrich students' understanding of how to use GenAI effectively. This integration can optimize opportunities for students to apply GenAI tools into authentic, hands-on learning tasks, thereby addressing the issue of limited mastery experiences. In addition, course rubrics with AI integration should focus more on students' critical engagement with tasks rather than mere task completion. This adaptation can discourage students from overreliance on GenAI tools and foster their reflective and critical thinking skills. By aligning instructional design with digital competence standards, educators can help students improve their confidence and responsibility in AI-assisted learning.

Theoretical implications

This study contributes to the theoretical understanding of technology acceptance in education by challenging existing findings and extending the TAM model framework. Notably, one of the findings in this study contradicts the current research by Liu and Ma (2023) regarding the relationship between perceived ease of use and attitude in the context of using ChatGPT. This discrepancy highlights the need to revisit and refine TAM constructs when applied to AI-driven learning contexts. Moreover, the impact of PEU and PU explained 61% of the variance in ATT, while ATT accounted for 28% of the variance in ASE. These results confirm the foundation role of TAM in understanding students' acceptance of ChatGPT. However, they also suggest that additional factors beyond PEU and PU might influence students' ATT and ASE. Further research should therefore consider extended versions of TAM, such as TAM2 or UTAUT, to explore other factors like facilitating condition and social influence, especially when the GenAI tools are officially integrated into institutional policies and curricula. Such investigations would provide a more comprehensive understanding of how ChatGPT and similar technologies can foster students' ATT toward learning and ASE within the learning environment.

CONCLUSION

This study explored how Vietnamese students used ChatGPT to support their learning and examined the impact of their acceptance of the tool on their ASE. It offers valuable insights into students' experiences with ChatGPT for personalized learning. Additionally, the study confirms the relationships among key TAM constructs, including PEU, PU, and ATT within the framework. Specifically, PEU predicts PU, and both PEU and PU predicted ATT, the only construct that directly affects students' ASE. Meanwhile, PEU, and PU indirectly influenced ASE through ATT. The findings also reveal that students with a positive ATT toward using ChatGPT tend to have higher ASE.

In terms of the significance of the study, this study provides a reference for educators and policymakers in the ongoing debate about the integration of ChatGPT into Vietnamese higher education. The findings suggest that students' positive acceptance of ChatGPT can enhance their learning self-efficacy. In this perspective, while concerns regarding academic integrity and dehumanization remain, it is necessary to train students effectively and responsibly using the tool. In other words, if ChatGPT is used appropriately, it can enhance students' confidence in their learning, potentially leading to greater academic success.

Despite its contributions, this study has several limitations. Firstly, the findings are primarily based on self-reported data. While this method of data collection can provide researchers with benefits, such as reduced costs and the ability to collect data from a large number of participants, it also has several drawbacks, including potential issues with memory recall issues and participants' responses influenced by social desirability (Pekruna, 2020). These factors may affect the reliability of the results. However, our thorough clarification of the purposes of the research and the assurance of confidentiality would create a sense of ease, which encourages the participants to share their perspectives openly (Dörnyei & Taguchi, 2009), which can lessen biases. To mitigate these potential biases further, research should incorporate diverse data collection methods to triangulate the results. Another limitation is that our study is a cross-sectional research design, which allows researchers to collect data at a single point in time. This approach limits the generalization of the findings to other times and contexts. Especially, with the introduction of the 2025 Digital Competence Framework for Learners, students in the future courses can receive more structured guidance and training on using GenAI tools for learning, which could impact on their PEU, PU, ATT and ASE differently. Finally, due to the nature of the time conducting this research when the official consistent guidelines had not yet been provided, the current study employed TAM by David (1990), ignoring the possibility influence of external factors such as facilitating condition and social influences. Therefore, further studies should explore how both external and internal factors influence students' learning outcomes like academic self-efficacy.

THE AUTHORS

Le Thi Truc Mai is a lecturer of English in the Department of English, FPT University, Can Tho Campus, Vietnam. Her research interests include virtual learning, feedback engagement and educational technology. She is also particularly interested in exploring the role of computer-assisted feedback in an online language learning environment.
mailtt15@fe.edu.vn

Tran Van Khue is a lecturer of English in the Department of English, FPT University, Can Tho Campus, Vietnam. His research interests involve virtual learning, feedback and educational technology.
khuetv@fe.edu.vn

REFERENCES

Agbong-Coates, I. J. G. (2024). ChatGPT integration significantly boosts personalized learning outcomes: A Philippine study. *International Journal of Educational Management and Development Studies, 5*(2), 165–186. https://doi.org/10.53378/353067

Al-Badi, A., & Khan, A. (2022). Perceptions of learners and instructors towards artificial intelligence in personalized learning. *Procedia Computer Science, 201*, 445–451. https://doi.org/10.1016/j.procs.2022.03.058

An, Y., Yu, J. H., & James, S. (2025). Investigating the higher education institutions' guidelines and policies regarding the use of generative AI in teaching, learning, research, and administration. *International Journal of Educational Technology in Higher Education, 22*(1), Article 10. https://doi.org/10.1186/s41239-025-00507-3

Anders, B. (2023). *ChatGPT AI in education: What it is and how to use it in the classroom.* Sovorel Publising.

Atlas, S. (2023). *ChatGPT for higher education and professional development: A guide to conversational AI.* https://digitalcommons.uri.edu/cgi/viewcontent.cgi?article=1547&context=cba_facpubs

Ayeni, O. O., Al Hamad, N. M., Chisom, O. N., Osawaru, B., & Adewusi, O. E. (2024). AI in education: A review of personalized learning and educational technology. *GSC Advanced Research and Reviews, 18*(2), 261–271. https://doi.org/10.30574/gscarr.2024.18.2.0062

Bandura, A. (1997). *Bandura: Self-efficacy: The exercise of control*. Freeman.

Bauer, D., Arnold, J., & Kremer, K. (2018). Consumption-intention formation in education for sustainable development: An adapted model based on the theory of planned behavior. *Sustainability, 10*(10), 1–13. https://doi.org/10.3390/su10103455

Bouzar, A., EL Idrissi, K., & Ghourdou, T. (2024). ChatGPT and academic writing self-efficacy: Unveiling correlations and technological dependency among postgraduate students. *Arab World English Journal (AWEJ), Special Issue on ChatGPT,* 225–236. https://dx.doi.org/10.24093/awej/ChatGPT.15

Chan, J. C. Y., & Lam, S. (2010). Effects of different evaluative feedback on students' self-efficacy in learning. *Instructional Science, 38*(1), 37–58. https://doi.org/10.1007/s11251-008-9077-2

Chang, C., Hwang, G., & Gau, M. (2022). Promoting students' learning achievement and self-efficacy: A mobile chatbot approach for nursing training. *British Journal of Educational Technology, 53*(1), 171–188. https://doi.org/10.1111/bjet.13158

Chomsky, N., Roberts, I., & Watumull, J. (2023). *Noam Chomsky: The false promise of ChatGPT.* The New York Times. https://edisciplinas.usp.br/pluginfile.php/7614933/mod_resource/content/1/Opinion%20_%20Noam%20Chomsky_%20The%20False%20Promise%20of%20ChatGPT%20-%20The%20New%20York%20Times.pdf

Creswell, J. W. (2009). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage. https://repository.vnu.edu.vn/handle/VNU_123/84779

Cresswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches.* Sage Publications.

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

Dörnyei, Z., & Taguchi, T. (2009). *Questionnaires in second language research: Construction, administration, and processing.* Routledge.

Elias, S. M., & MacDonald, S. (2007). Using past performance, proxy efficacy, and academic self-efficacy to predict college performance. *Journal of Applied Social Psychology, 37*(11), 2518–2531. https://doi.org/10.1111/j.1559-1816.2007.00268.x

Elliot, A. J., Murayama, K., & Pekrun, R. (2011). A 3 X 2 achievement goal model. *Journal of Educational Psychology, 103*(3), 632–648. https://doi.org/10.1016/j.compedu.2021.104252

Evangelista, E. D. L. (2025). Ensuring academic integrity in the age of ChatGPT: Rethinking exam design, assessment strategies, and ethical AI policies in higher education. *Contemporary Educational Technology, 17*(1), 1–19. https://doi.org/10.30935/cedtech/15775

Firat, M. (2023). What ChatGPT means for universities: Perceptions of scholars and students. *Journal of Applied Learning and Teaching, 6*(1), 1–7. https://doi.org/10.37074/jalt.2023.6.1.22

Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational context: A systematic literature review. *British Journal of Educational Technology, 50*(5), 2572–2593. https://doi.org/10.1111/bjet.12864

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough?: An experiment with data saturation and variability. *Field Methods, 18*(1), 59–82. https://doi.org/10.1177/1525822x05279903

Guyah, P., Mari, J. S., & Ginga, U. A. (2021). Effect of personalized learning instructional strategy on self-efficacy in mole concept among chemistry students in Zaria, Nigeria. *Nigerian Research Journal of Chemical Sciences, 9*(1), 165–172.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2018). *Multivariate data analysis* (8th ed.). Annabel Ainscow.

Hall, A., Uribe-Flórez, L., & Rice, K. (2019). Studying teachers' self-efficacy and experience while empowering technology use through personalized professional learning. J*ournal of Technology and Teacher Education, 27*(3), 373–413.

Hanham, J., Lee, C. B., & Teo, T. (2021). The influence of technology acceptance, academic self-efficacy, and gender on academic achievement through online tutoring. *Computers & Education, 172*(2021), 1–14. https://doi.org/10.1016/j.compedu.2021.104252

Heaton, J. (2022). "*Pseudonyms are used throughout": A footnote, unpacked. *Qualitative Inquiry, 28*(1), 123–132. https://doi.org/10.1177/10778004211048379

Hennink, M., & Kaiser, B. N. (2022). Sample sizes for saturation in qualitative research: A systematic review of empirical tests. *Social Science & Medicine, 292*, Article 114523. https://doi.org/10.1016/j.socscimed.2021.114523

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Ibrahim, H., Asim, R., Zaffar, F., Rahwan, T., & Zaki, Y. (2023). Rethinking homework in the age of artificial intelligence. *IEEE Intelligent Systems, 38*(2), 24–27. https://doi.org/10.1109/MIS.2023.3255599

Le, T. T. M., & Tran, V. K. (2024). Vietnamese university students' perceptions of ChatGPT for homework assistance. *International Journal of Interactive Mobile Technologies, 18*(15), 190–204. https://doi.org/10.3991/ijim.v18i15.48819

Lee, Y.-F., Hwang, G.-J., & Chen, P.-Y. (2022). Impacts of an AI-based chabot on college students' after-class review, academic performance, self-efficacy, learning attitude, and motivation. *Educational Technology Research and Development, 70*(5), 1843–1865. https://doi.org/10.1007/s11423-022-10142-8

Li, K. C., & Wong, B. T.-M. (2021). Features and trends of personalised learning: A review of journal publications from 2001 to 2018. *Interactive Learning Environments, 29*(2), 182–195. https://doi.org/10.1080/10494820.2020.1811735

Liebrenz, M., Schleifer, R., Buadze, A., Bhugra, D., & Smith, A. (2023). Generating scholarly content with ChatGPT: Ethical challenges for medical publishing. *The Lancet Digital Health, 5*(3), e105–e106. https://doi.org/10.1016/S2589-7500(23)00019-5

Limo, F. A. F., Tiza, D. R. H., Roque, M. M., Herrera, E. E., Murillo, J. P. M., Huallpa, J. J., Flores, V. A. A., Castillo, A. G. R., Peña, P. F. P., & Carranza, C. P. M. (2023). Personalized tutoring: ChatGPT as a virtual tutor for personalized learning experiences. *Social Space, 23*(1), 293–312.

Liu, G., & Ma, C. (2023). Measuring EFL learners' use of ChatGPT in informal digital learning of English based on the technology acceptance model. *Innovation in Language Learning and Teaching, 18*(2), 1–14. https://doi.org/10.1080/17501229.2023.2240316

Meng, Q., & Zhang, Q. (2023). The influence of academic self-efficacy on university students' academic performance: The mediating effect of academic engagement. *Sustainability, 15*(7), 1–14. https://doi.org/10.3390/su15075767

Menon, D., & Shilpa, K. (2023). "Chatting with ChatGPT": Analyzing the factors influencing users' intention to use the open AI's ChatGPT using the UTAUT model. *Heliyon, 9*(11), 1–19. https://doi.org/10.1016/j.heliyon.2023.e20962

Midgley, C., Maehr, M. L., Hruda, L. Z., Anderman, E., Anderman, L., Freeman, K. E., & Urdan, T. (2000). *Manual for the patterns of adaptive learning scales* (pp. 734–763). University of Michigan. https://www.academia.edu/download/3479746/pals_2000_v12word97.pdf

MOET. (2025). *Digital competence framework in Vietnam* (Circular No. 02/2025/TT-BGDDT). https://thuvienphapluat.vn/van-ban/EN/Giao-duc/Circular-02-2025-TT-BGDDT-Digital-Competence-Framework/646278/tieng-anh.aspx

Ngo, T. T. A. (2023). The perception by university students of the use of ChatGPT in education. *International Journal of Emerging Technologies in Learning (Online), 18*(17), 4–19. https://doi.org/10.3991/ijet.v18i17.39019

Nguyen, Q. T. (2024). Artificial intelligence (AI) in education: A case study on ChatGPT's influence on student learning behaviors. *Educational Process International Journal, 13*(2), 105–121. https://doi.org/10.22521/edupij.2024.132.7

Parsakia, K. (2023). The effect of chatbots and AI on the self-efficacy, self-esteem, problem-solving and critical thinking of students. *Health Nexus, 1*(1), 71–76. https://doi.org/10.61838/kman.hn.1.1.11

Peechapol, C., Na-Songkhla, J., Sujiva, S., & Luangsodsai, A. (2018). An exploration of factors influencing self-efficacy in online learning: A systematic review. *International Journal of Emerging Technologies in Learning (Online), 13*(9), 64–86. https://doi.org/10.3991/ijet.v13i09.8351

Pekruna, R. (2020). Self-report is indispensable to assess students' learning. *Frontline Learning Research, 8*(3), 185–193. https://doi.org/10.14786/flr.v8i3.637

Pham, V. P. H., & Le, A. Q. (2024). ChatGPT in language learning: Perspectives from Vietnamese students in Vietnam and the USA. *International Journal of Language Instruction, 3*(2), 59–72. http://dx.doi.org/10.54855/ijli.24325

Pratama, M. P., Sampelolo, R., & Lura, H. (2023). Revolutionizing education: Harnessing the power of artificial intelligence for personalized learning. *Klasikal: Journal of Education, Language Teaching and Science, 5*(2), 350–357. https://doi.org/10.52208/klasikal.v5i2.877

Regatto-Bonifaz, J., & Viteri-Miranda, V. (2023). Attitude towards technology and its relationship with academic self-efficacy in Ecuadorian university students. *Journal of Namibian Studies: History Politics Culture, 33*(3), 3216–3233. https://doi.org/10.59670/jns.v33i.2807

Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education? *Journal of Applied Learning and Teaching, 6*(1), 342–363. https://doi.org/10.37074/jalt.2023.6.1.9

Sana, F., Weston, T., & Cepeda, N. J. (2013). Laptop multitasking hinders classroom learning for both users and nearby peers. *Computers & Education, 62*(2013), 24–31. https://doi.org/10.1016/j.compedu.2012.10.003

Scherer, R., & Teo, T. (2019). Unpacking teachers' intentions to integrate technology: A meta-analysis. *Educational Research Review, 27*(2019), 90–109. https://doi.org/10.1016/j.edurev.2019.03.001

Su, J., & Yang, W. (2023). Unlocking the power of ChatGPT: A framework for applying generative AI in education. *ECNU Review of Education, 6*(3), 355–366. https://doi.org/10.1177/20965311231168423

Talsma, K., Schüz, B., Schwarzer, R., & Norris, K. (2018). I believe, therefore I achieve (and vice versa): A meta-analytic cross-lagged panel analysis of self-efficacy and academic performance. *Learning and Individual Differences, 61*(2018), 136–150. https://doi.org/10.1016/j.lindif.2017.11.015

Tiwari, C. K., Bhat, M. A., Khan, S. T., Subramaniam, R., & Khan, M. A. I. (2024). What drives students toward ChatGPT? An investigation of the factors influencing adoption and usage of ChatGPT. *Interactive Technology and Smart Education, 21*(3), 333–355. https://doi.org/10.1108/ITSE-04-2023-0061

Tran, M. T., & Duong, H. L. (2024). Examining the effects of employing ChatGPT on university students in Vietnam. In M. T. Tran (Ed.), *Adaptive learning technologies for higher education* (pp. 206–221). IGI Global. https://www.igi-global.com/chapter/examining-the-effects-of-employing-chatgpt-on-university-students-in-vietnam/353024

Travis, J., Kaszycki, A., Geden, M., & Bunde, J. (2020). Some stress is good stress: The challenge-hindrance framework, academic self-efficacy, and academic outcomes. *Journal of Educational Psychology, 112*(8), 1632–1643. https://doi.org/10.1037/edu0000478

Ünal, B., Kavanoz, S., Güler, A., & Karabulut, N. (2019). High school students' attitudes towards ICT and media tools in learning English and academic self-efficacy beliefs. *RumeliDE Dil ve Edebiyat Araştırmaları Dergisi, 17,* 298–308. https://doi.org/10.29000/rumelide.656758

Urban, M., Děchtěrenko, F., Lukavskỳ, J., Hrabalová, V., Svacha, F., Brom, C., & Urban, K. (2024). ChatGPT improves creative problem-solving performance in university students: An experimental study. *Computers & Education, 215*(2024), 1–15. https://doi.org/10.1016/j.compedu.2024.105031

van der Vorst, T., & Jelicic, N. (2019, June 16–19). *Artificial intelligence in education: Can AI bring the full potential of personalized learning to education?* [Paper presentation]. 30th European Conference of the International Telecommunications Society (ITS): "Towards a connected and automated society", Helsinki, Finland. https://hdl.handle.net/10419/205222

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

Vo, T. K. A., & Nguyen, H. (2024). Generative artificial intelligence and ChatGPT in language learning: EFL students' perceptions of technology acceptance. *Journal of University Teaching and Learning Practice, 21*(6), Article 811. https://doi.org/10.53761/fr1rkj58

Xie, H., Chu, H.-C., Hwang, G.-J., & Wang, C.-C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers & Education, 140*(2019), Article 103599. https://doi.org/10.1016/j.compedu.2019.103599

Xu, X., Wang, X., Zhang, Y., & Zheng, R. (2024). Applying ChatGPT to tackle the side effects of personal learning environments from learner and learning perspective: An interview of experts in higher education. *Plos One, 19*(12), Article e0315764. https://doi.org/10.1371/journal.pone.0295646

Yildiz-Durak, H. (2023). Conversational agent-based guidance: Examining the effect of chatbot usage frequency and satisfaction on visual design self-efficacy, engagement, satisfaction, and learner autonomy. *Education and Information Technologies, 28*(1), 471–488. https://doi.org/10.1007/s10639-022-11149-7

Yilmaz, H., Maxutov, S., Baitekov, A., & Balta, N. (2023). Student attitudes towards ChatGPT: A technology acceptance model survey. *International Educational Review, 1*(1), 57–83. https://doi.org/10.58693/ier.114

Yilmaz, R., & Yilmaz, F. G. K. (2023). The effect of generative artificial intelligence (AI)-based tool use on students' computational thinking skills, programming self-efficacy and motivation. *Computers and Education: Artificial Intelligence, 4*(2023), Article 100147. https://doi.org/10.1016/j.caeai.2023.100147

Yokoyama, S. (2019). Academic self-efficacy and academic performance in online learning: A mini review. *Frontiers in Psychology, 9*, Article 2794. https://doi.org/10.3389/fpsyg.2018.02794

Zhang, L., Basham, J. D., & Yang, S. (2020). Understanding the implementation of personalized learning: A research synthesis. *Educational Research Review, 31,* Article 100339. https://doi.org/10.1016/j.edurev.2020.100339

Zimmerman, M. (2018). *Teaching AI: Exploring new frontiers for learning*. International Society for Technology in Education.

Zou, M., & Huang, L. (2023). To use or not to use? Understanding doctoral students' acceptance of ChatGPT in writing through technology acceptance model. *Frontiers in Psychology, 14*, Article 1259531. https://doi.org/10.3389/fpsyg.2023.1259531

Appendix 1
Constructs of TAM model adapted from Liu and Ma (2023)

Perceived ease of use

1. I think ChatGPT is very easy to use.
2. I find the information from ChatGPT easy to follow.
3. Learning how to use ChatGPT is simple for me.
4. I feel that using ChatGPT is clear and straightforward.

Perceived usefulness

1. I believe ChatGPT can enhance the quality of my studies.
2. I think ChatGPT can make my learning process more effective.
3. I feel that ChatGPT can offer me additional learning opportunities.
4. I think ChatGPT can enhance my ability to learn.

Attitude

1. ChatGPT is a highly appealing learning tool.
2. Learning with ChatGPT is fascinating.
3. I enjoy using ChatGPT as part of my studies.
4. I think using ChatGPT for learning is a great idea.

Appendix 2
Academic Self-Efficacy scale, adapted from the Patterns of Adaptive Learning Scales developed by Midgley et al. (2000)

1. I am confident that I can excel in the skills being taught in class this year.
2. I'm sure I can work out how to do the hardest classwork.
3. I can finish almost all the classwork if I keep going.
4. Even if the work is hard, I can learn it.
5. I can do the tough work in this class if I try.