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Factors influencing the use of ChatGPT in student learning in Vietnam

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ABSTRACT

This study explores the factors affecting students' use of ChatGPT in educational settings, with a specific focus on higher education in Vietnam. It applies an extended version of the Technology Acceptance Model (TAM), which includes mobility and convenience in addition to the traditional concepts of perceived usefulness and perceived ease of use. The goal is to better understand what encourages students to adopt ChatGPT. A total of 3,550 students participated in a survey, and the data were analyzed using structural equation modeling to examine the relationships between the key factors. The results show that perceived usefulness, mobility, and convenience have strong positive effects on students' intention to use ChatGPT, while perceived ease of use has a small negative effect. Demographic factors, such as the students' academic year, also influence adoption patterns. The study highlights the importance of promoting ChatGPT's practical benefits and ease of access to encourage wider use. It ends with theoretical and practical insights and offers suggestions for future research on the use of AI tools in education.

1. Introduction

The transformative power of Information and Communication Technology (ICT) and the rapid evolution of artificial intelligence (AI) tools have ushered in a new era for education, revolutionizing the way knowledge is delivered, accessed, and applied (Alam and Mohanty, 2023). Among these innovations, ChatGPT, a state-of-the-art AI-powered language model, stands out as a versatile tool capable of assisting users with tasks ranging from answering complex questions to generating detailed, context-specific content (Annepaka and Pakray, 2024). Its ability to deliver instant, accurate, and tailored support has positioned ChatGPT as a potential game-changer in educational contexts (Hadi Mogavi et al., 2024; Yu, 2024).

Globally, the adoption of AI tools in education is accelerating, driven by their capacity to enhance learning experiences, increase efficiency, and offer personalized support (Ellikkal and Rajamohan, 2024; Rahiman and Kodikal, 2024; Wang et al., 2024). Tools like ChatGPT empower students by providing immediate access to information, facilitating complex problem-solving, and enabling continuous learning at their own pace (Hadi Mogavi et al., 2024; Rawas and AlSaeed, 2024). This makes AI tools indispensable in modern education, especially higher education, where students must balance demanding academic workloads with other responsibilities. For instance, the global AI in the education market was estimated at USD 5.88 billion in 2024 and is projected to grow at a compound annual growth rate (CAGR) of 31.2% from 2025 to 2030, reflecting their increasing integration into learning ecosystems.

In Vietnam, digital transformation in education has been a strategic priority, with policies aimed at modernizing curricula and equipping students with the digital skills needed for a global economy. AI tools like ChatGPT are well-aligned with these goals, offering significant potential to address educational challenges. ChatGPT offers several advantages to students' learning in Vietnam, including enhanced accessibility to information, personalized learning experiences, and support for language development, particularly in English proficiency. Its ability to provide instant responses and explanations helps students grasp complex concepts quickly, making learning more efficient and effective. However, there are also disadvantages, such as the risk of reduced critical thinking skills due to overreliance on AI-generated answers and the potential for misinformation if students do not verify the accuracy

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of the content. Moreover, the lack of regulation in AI-driven learning raises concerns about ethical use, academic integrity, and data privacy. While ChatGPT is a valuable tool for education, its effectiveness depends on students' responsible usage and proper guidance from educators (Maheshwari, 2024; Tri et al., 2025).

Research on technology adoption frameworks, such as the Technology Acceptance Model (TAM) (Davis, 1989), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and their extensions, has consistently emphasized the importance of perceived usefulness and ease of use as determinants of user behavior. However, traditional models often overlook emerging variables like mobility and convenience, which have become increasingly relevant in today's digital learning environments (Maheshwari, 2024; Shahzad et al., 2024). Additionally, demographic factors, including the academic year and frequency of technology use, may significantly influence how students engage with AI tools, but these aspects remain underexplored in the existing literature (Pellas, 2023).

This study aims to fill these gaps by investigating the factors that influence students' behavior when using ChatGPT in educational settings, utilizing an extended TAM framework. By incorporating mobility and convenience alongside traditional constructs, the research provides a nuanced understanding of the drivers of ChatGPT adoption. Furthermore, it examines the role of demographic variables to uncover unique patterns and insights into user behavior in the context of Vietnamese higher education.

The remainder of this paper is organized as follows: Section 2 provides an in-depth examination of the theoretical background and key constructions. Section 3 outlines the methodology, including data collection and analytical techniques. Section 4 presents the empirical findings, followed by Section 5, which discusses the main results and offers practical and theoretical implications. Finally, Section 6 concludes the paper with a summary of limitations and directions for future research.

2. Theoretical background

The TAM, introduced by Davis (1989), has been widely used to explain users' acceptance and use of new technologies. TAM primarily emphasizes two key constructs: perceived usefulness (PU) and perceived ease of use (PEOU). PU refers to the degree to which a person believes that using a particular system would enhance their performance. At the same time, PEOU represents the extent to which a person believes that using the system would require minimal effort. These two constructs are foundational in predicting behavioral intention and actual use of technology.

To better reflect the unique characteristics of AI tools, such as ChatGPT, in educational contexts, this study extends the TAM by incorporating an additional construct: mobility and convenience (MC). MC refers to the flexibility and ease with which students can access ChatGPT across various devices and platforms, allowing them to integrate AI assistance into their learning routines regardless of time or location. The decision to integrate MC into the traditional TAM framework is grounded in the growing importance of ubiquitous and on-demand learning among university students. In contrast to traditional digital platforms, generative AI tools like ChatGPT are often accessed via smartphones, tablets, and browser-based interfaces, enabling spontaneous, portable, and seamless interactions (Zare et al., 2022). As students increasingly engage in micro-learning, multitask during commutes, and seek immediate academic assistance, the value of mobility and platform accessibility becomes critical. Prior studies have also emphasized that mobile usability and contextual convenience are significant antecedents to technology acceptance, particularly in educational settings (An et al., 2025; Lai and Hwang, 2014; Yu et al., 2022). Integrating MC into TAM helps better capture how modern learners interact with AI tools beyond traditional desktop-based systems. Thus, MC is modeled here as a direct predictor of students' behavior of use (BU), reflecting its independent influence on technology engagement.

Furthermore, this study also examines the influence of selected demographic factors, including gender, academic year, and frequency of ChatGPT usage in learning. These variables provide additional explanatory power in understanding patterns of AI adoption among students in higher education.

2.1. Recent literature on AI and ChatGPT adoption in higher education

Recent studies conducted in 2024–2025 have shed new light on the adoption of generative AI tools, such as ChatGPT, in higher education. Guettala et al. (2024) found that students frequently use ChatGPT to support learning activities, such as drafting assignments and preparing for exams. Their findings also emphasized concerns about academic integrity and the necessity for institutional policies to guide responsible use. Similarly, Ghalia et al. (2024) conducted interviews with both students and instructors, revealing diverse usage patterns and evolving norms that highlight the role of contextual and disciplinary factors in AI integration.

Shuhaiber et al. (2025) conducted a global survey and found that while students appreciate ChatGPT for brainstorming and simplifying complex concepts, they remain skeptical about its factual accuracy and rely more heavily on it for non-assessment-related learning. From an institutional perspective, Liew et al. (2024) argued that universities must adopt systems thinking to manage AI transitions effectively, ensuring alignment between educational goals, resources, and governance. Jin et al. (2025) further called for comprehensive innovation diffusion frameworks to shape strategic adoption, policy response, and stakeholder engagement in higher education. These recent insights complement the TAM-based approach of this study and underscore the importance of situating traditional technology acceptance frameworks within the rapidly evolving and ethically complex landscape of AI-enhanced learning.

2.2. Research hypotheses and framework

PU refers to how users perceive ChatGPT as enhancing their academic performance. Previous studies have consistently demonstrated that PU is a significant predictor of technology adoption (Davis, 1989; Quang Doan et al., 2024; Linh and Huyen, 2025). For example, a study by Songkram et al. (2023) highlighted that PU significantly BU toward adopting educational technologies. Almulla (2024) similarly found that PU strongly impacts students' willingness to integrate AI tools into their learning processes. Therefore, the following hypothesis can be formulated:

H1: PU positively influences students' BU of ChatGPT.

PEOU refers to the degree to which users perceive technology as easy to use and require minimal effort. In the context of educational technologies, when students find tools intuitive and user-friendly, their behavior of use increases (Ayanwale and Ndlovu, 2024; Valle et al., 2024). Maheshwari (2024) also identified PEOU as a critical factor influencing the adoption of AI-driven tools in Vietnamese higher education. Therefore, we propose the following hypothesis:

H2: PEOU positively influences students' BU of ChatGPT.

MC refers to the accessibility and flexibility provided by ChatGPT across various devices and locations. As highlighted by Mercan et al. (2024) and Sisouvong and Pasanchay (2024), mobility enables seamless technology integration into students' daily routines, fostering greater engagement and utilization. Similarly, studies by Alalwan et al. (2015) and Kim and Kankanhalli (2009) emphasized that mobile accessibility significantly enhances the perceived value of educational technologies, encouraging adoption. Thus, we propose the following hypothesis:

H3: MC positively influences students' BU of ChatGPT.

Demographic factors also play a significant role in influencing the adoption of ChatGPT. For instance, gender differences in technology adoption have been widely observed, with males often reporting higher levels of perceived usefulness and ease of use (Gefen et al., 2003; Venkatesh et al., 2003). Students in different school years exhibit varying levels of familiarity and confidence with technology, which can potentially impact their adoption behavior (Baidoo-Anu et al., 2024; Pellas, 2023; Tsourela and Roumeliotis, 2015). Moreover, the frequency of technology used in academic contexts indicates students' comfort and readiness to engage with AI tools (Widodo and Akbar, 2024). In line with the above argument, we propose the following hypothesis:

H4: Male students positively influence the BU of ChatGPT.
H5: The school year has a positive influence on students' BU of ChatGPT.
H6: The frequency of ChatGPT use positively influences students' BU of ChatGPT.

Building on these insights, this study employs TAM constructs (PU, PEOU, and MC) alongside demographic variables (gender, school year, and frequency of use) to examine the factors influencing the use behavior of ChatGPT among students in Vietnam. The complete research framework is illustrated in Fig. 1.

3. Methodology

3.1. Data collection

This study collected data from students currently enrolled at Phenikaa University, one of Vietnam's leading institutions, which has over 25,000 students. The university comprises four schools and three faculties, offering over 60 academic programs across a broad range of disciplines. Phenikaa University is recognized for its strong emphasis on research and the integration of advanced technologies into education, making it an ideal setting for this study.

First, the survey questionnaire was carefully designed based on the theoretical foundation and relevant studies on the factors influencing the BU of ChatGPT. The constructions examined in this study were BU, PU, and PEOU, and MC. The questionnaire items were refined through a review of existing literature and expert consultations with professionals in educational technology and AI applications, ensuring content accuracy and clarity.

Second, an initial pilot test was conducted involving 100 students from Phenikaa University. Feedback from the pilot test participants was used to make necessary adjustments to the questionnaire, including rephrasing ambiguous items and optimizing the structure for improved comprehension.

Third, the official survey was administered online from December 2024 to January 2025. The questionnaire link was distributed to Phenikaa University students through email and institutional communication channels. A total of 4,554 responses were collected. After data cleaning to remove incomplete and invalid responses, 3,550 completed surveys were deemed usable, meeting the study's quality requirements. The sample size was determined according to Hair (2011), who suggested a minimum ratio of 20:1 for the number of responses to the number of variables. With seven constructions examined in this study, the required sample size was 140, far exceeded by the final usable dataset.

Respondents were informed about the purpose of the study and provided consent before participating. The survey collected demographic information, including gender, school year, and frequency of technology use, alongside responses to items measuring the TAM constructs (Belief in Use, Perceived Usefulness, Perceived Ease of Use, and Motivation to Continue Use). Participation was voluntary, and students were assured of the confidentiality and anonymity of their responses.

Phenikaa University's diverse academic programs and large student body provided a rich context for exploring the adoption of technology. Its proactive efforts to integrate AI tools into education make it an exemplary institution for examining the factors influencing the behavior of use of ChatGPT. The comprehensive data collected offers valuable insights into students' adoption and usage patterns of AI-driven educational tools.

3.2. Data description

Table 1 presents the demographic characteristics of the survey respondents. According to the gender distribution, 38.84% of respondents are male (1,301 individuals), while the remaining 61.16% are female (2,049 individuals). This higher proportion of female respondents is consistent with general trends observed in university student populations, including those at Phenikaa University. Regarding the academic year, most respondents are in their second year of study, accounting for 31.91%, followed by third-year students at 28.00%. First-year students constitute 18.96%, and fourth-year students make up 20.54%. A small percentage, 0.60% (20 individuals), are in their fifth year of study. This distribution provides a balanced representation of students across different academic stages, a characteristic also reflected within Phenikaa University's diverse programs.

Regarding the frequency of ChatGPT use in learning, most respondents reported using it occasionally or regularly. Specifically, 45.82% use ChatGPT sometimes, while 32.24% reported weekly usage. Daily users constitute 14.51%, indicating a significant level of integration into their learning routines. Conversely, 6.21% rarely use ChatGPT, and 1.22% reported not using it.

These demographic characteristics highlight a diverse and representative sample of university students. The data provides critical insights into how factors such as gender, academic year, and ChatGPT usage frequency influence students' behavior of use in learning contexts.

3.3. Statistical methods

Structural Equation Modeling (SEM) is an advanced statistical approach widely used to examine complex relationships among variables within a theoretical framework. Unlike first-generation techniques, such as regression analysis, SEM enables the simultaneous evaluation of multiple dependent and independent variables, making it ideal for analyzing the constructs in this study.

Table 1: Sample demographics

Variables	Category	Frequency	Percent
Gender	Male	1,301	38.84
	Female	2,049	61.16
School year (academic year of student)	Year 1	635	18.96
	Year 2	1,069	31.91
	Year 3	938	28.00
	Year 4	688	20.54
	Year 5	20	0.60
Frequency (frequency of using ChatGPT in learning)	Do not use	41	1.22
	Rarely	208	6.21
	Sometimes	1,535	45.82
	Weekly	1,080	32.24
	Daily	486	14.51

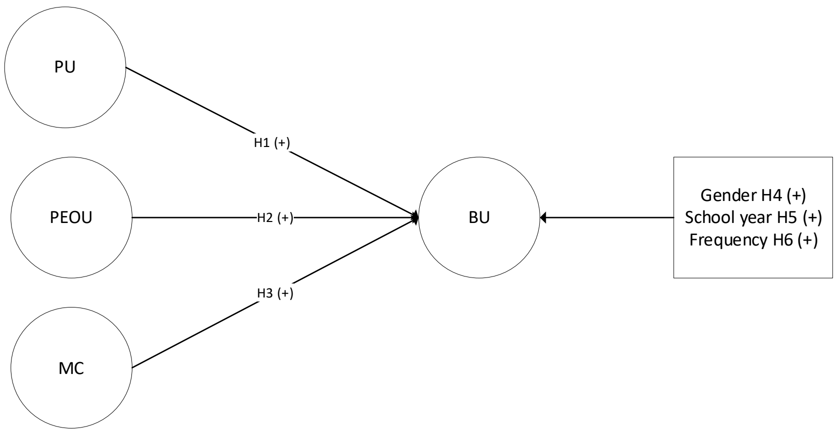


Fig. 1: Conceptual framework

The research model includes four key constructs: BU, PU, PEOU, and MC. These constructions are multidimensional and require measurement through observable indicators. SEM was chosen because it effectively addresses latent variables and their relationships while accounting for measurement errors, providing deeper insights into the data.

To ensure the robustness of the model, the analysis followed a two-step process. First, exploratory factor analysis (EFA) was conducted to identify underlying structures and refine the measurement items. This step ensured that all indicators were aligned with their respective constructs. Second, confirmatory factor analysis (CFA) was performed to validate the measurement model.

Key indicators, including factor loadings, composite reliability (CR), and average variance extracted (AVE), were examined to assess the validity and reliability of the constructs. Our study implemented the SEM process using Stata 17, a powerful statistical software that supports advanced modeling techniques.

4. Results

4.1. Reliability and validity test

The results presented in Table 2 demonstrate that all factor loadings exceed the recommended threshold of 0.6, with Cronbach's alpha values ranging from 0.889 to 0.903. These values indicate strong internal consistency among the constructions, ensuring the reliability of the measurement items. Additionally, the Kaiser-Meyer-Olkin (KMO) measure yielded a value of 0.899, suggesting that the sampling adequacy is suitable for factor analysis. The Bartlett's sphericity test further confirmed the data's appropriateness for this analysis, with statistical significance at the 0.01 level. These findings validate the robustness of the factor structure utilized in this research.

Table 2: The results of Cronbach's alpha and EFA

Variable	Cronbach's alpha	BU	PU	PEOU	MC
BU1	0.894	0.848			
BU2	0.893	0.891			
BU3	0.893	0.859			
BU4	0.896	0.862			
PU1	0.892				0.827
PU2	0.893				0.776
PU3	0.892				0.834
PU4	0.895				0.729
PEOU1	0.901			0.800	
PEOU2	0.903			0.832	
PEOU3	0.900			0.872	
PEOU4	0.901			0.875	
MC1	0.891		0.866		
MC2	0.889		0.871		
MC3	0.889		0.738		
MC4	0.890		0.821		

CFA was conducted to further assess the validity and reliability of the constructions. Table 3 reports the CR and AVE for each construct. All CR values exceeded the acceptable threshold of 0.6, ranging from 0.878 to 0.943, consistent with the recommendations by Bagozzi and Yi (1988). The AVE values for all constructions were greater than 0.5, satisfying the criteria established by Fornell and Larcker (1981). These results confirm the model's convergent validity.

Table 3: Measurement model

Variables	Coefficient		OIM Standard error	P-value	CR	AVE
		BU			0.917	0.847
BU1	0.786		0.008	0.000		
BU2	0.864		0 .006	0.000		
BU3	0.912		0.005	0.000		
BU4	0.871		0.005	0.000		
		PU			0.910	0.716
PU1	0.867		0.009	0.000		
PU2	0.889		0.015	0.000		
PU3	0.832		0.009	0.000		
PU4	0.795		0.018	0.000		
		PEOU			0.878	0.643
PEOU1	0.783		0.018	0.000		
PEOU2	0.711		0.018	0.000		
PEOU3	0.839		0.017	0.000		
PEOU4	0.859		0.018	0.000		
		MC			0.943	0.716
MC1	0.844		0.011	0.000		
MC2	0.884		0.008	0.000		
MC3	0.967		0 .013	0.000		
MC4	0.882		0.008	0.000		

LR test of model vs. saturated: chi2(83) = 697.14; Prob > chi2 = 0.000

Goodness-of-fit indices were also evaluated to ensure the adequacy of the measurement model. The indices achieved satisfactory levels, including Comparative Fit Index (CFI) = 0.985, Tucker–Lewis

Index (TLI) = 0.978, Standardized Root Mean Square Residual (SRMR) = 0.033, and Root Mean Squared Error of Approximation (RMSEA) = 0.047. These values indicate the model's strong fit and suitability for further analysis.

In summary, the findings from Tables 2 and 3 demonstrate the high reliability and validity of the measurement model, providing a robust foundation for subsequent analyses of the factors influencing the adoption of ChatGPT in educational settings.

4.2. Structural equation model

Before testing the structural relationships, the model's overall fit was evaluated. The results demonstrated good model fit with the following indices: CFI = 0.925, TLI = 0.928, and RMSEA = 0.905. These findings confirm the adequacy and reliability of the structural model for examining hypothesized relationships.

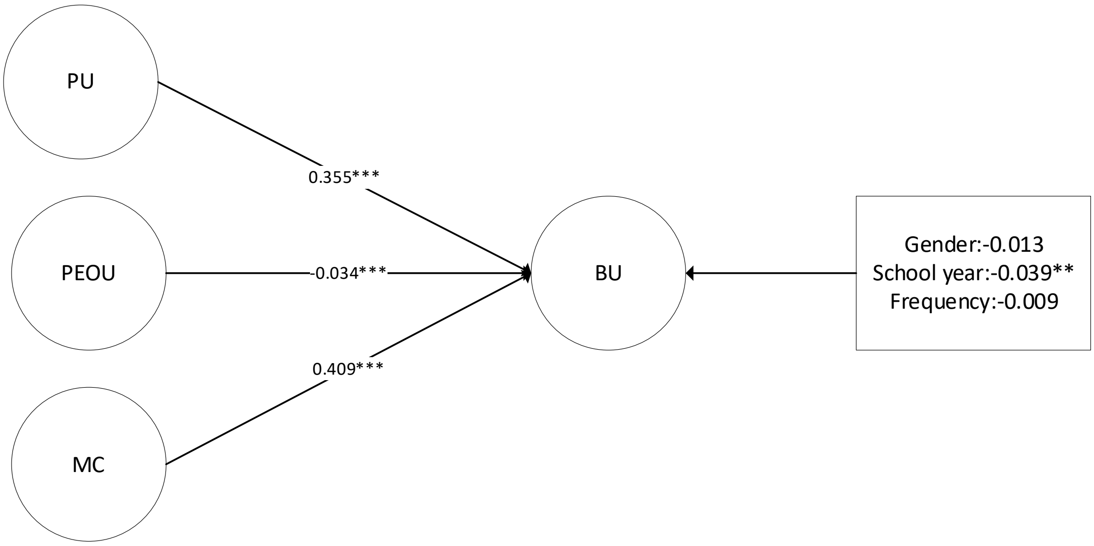
As shown in Table 4 and Fig. 2, several key relationships were identified. PU had a significant positive influence on the BU, demonstrating the critical role of PU in motivating students to adopt ChatGPT. MC also showed a strong positive effect on BU, highlighting the importance of flexible and accessible learning tools.

Table 4: Structural equation model results

Variables	Coefficient	Standard error	Z-value	P-value
Gender	-0.013	0.016	-0.80	0.426
School year	-0.039	0.016	-2.48	0.013
Frequency	-0.009	0.017	-0.58	0.562
PU	0.355	0.022	15.83	0.000
PEOU	-0.034	0.017	-1.97	0.049
MC	0.409	0.021	19.99	0.000

LR test of model vs. saturated: chi2(134) = 3197.60; Prob > chi2 = 0.000

Conversely, PEOU exhibited a slight negative effect on BU, suggesting that ease of use alone may not be the primary driver of adoption when other factors are at play. Among the control variables, the academic year of the students had a negative influence on BU, while gender and frequency of use were not statistically significant in predicting the behavior of use. Overall, the structural equation modeling results provide strong evidence for the influence of PU and MC on students' behavior in using ChatGPT while highlighting the nuanced role of PEOU and demographic factors. These findings contribute valuable insights into the factors driving the adoption of AI tools in educational contexts.



**: P < 0.01 (significant at the 1% level); ***: P < 0.001 (significant at the 0.1% level)

Fig. 2: The results of the structural equation model

4.3. Additional analysis

To address potential non-normality issues, we conducted Skewness-Kurtosis tests following the recommendations of Barnes et al. (2001) and Vieira (2011). Additionally, we employed a model cross-validation analysis as suggested by Diamantopoulos and Siguaw (2000). Our model's performance was assessed using multivariate normality tests, including Mardia's mSkewness and mKurtosis tests (m is for multivariable). The results confirmed that our model met the necessary normality assumptions.

$$Mardia\ mSkewness = 13.83363 chi2(816) = 7731.508 Prob > chi2 = 0.0000$$
$$Mardia\ mKurtosis = 428.0135 chi2(1) = 28503.744 Prob > chi2 = 0.0000$$

5. Discussion

5.1. The main findings

This study examined the factors influencing students' behavior using ChatGPT in educational settings by applying an extended Technology Acceptance Model. The empirical results highlighted the significant roles of perceived usefulness, perceived ease of use, and mobility and convenience in shaping user behavior.

H1. PU -> BU: Perceived usefulness was found to have a significant positive influence on BU, with a coefficient of 0.355 ($p < 0.001$). This suggests that students perceive ChatGPT as a tool that enhances their learning efficiency and academic performance. These findings align with prior studies (Almulla, 2024; Linh, 2024; Shahzad et al., 2024), emphasizing that when users recognize clear benefits in technology, their likelihood of adoption increases. Students particularly value ChatGPT for its ability to provide quick answers, summarize content, and support research tasks, making it a vital resource for academic purposes. This result is consistent with Maheshwari (2024), who found that perceived usefulness significantly impacted the adoption of e-learning systems among Vietnamese students. PU remains a central determinant of technology engagement in educational contexts, particularly when the tool offers apparent performance enhancement.

H2. PEOU -> BU: Perceived ease of use had a slight negative effect on BU, with a coefficient of -0.034 ($p = 0.049$). While this may seem counterintuitive, it indicates that ease of use alone is insufficient to drive adoption when students prioritize other attributes, such as utility and convenience. This result adds nuance to the TAM framework, suggesting that tangible benefits must complement simplicity. Similar observations were made by Ayanwale and Ndlovu (2024), Maheshwari (2024), and Valle et al. (2024), who argued that the impact of perceived ease of use diminishes when users are already familiar with technology. In the context of this study, students who were accustomed to using other AI tools might have placed less emphasis on the ease of use of ChatGPT. This suggests that for tools like ChatGPT, ease of use may not guarantee increased usage unless paired with trust and perceived credibility.

H3. MC -> BU: Mobility and convenience exhibited the strongest positive impact on BU, with a coefficient of 0.409 ($p < 0.001$). This demonstrates that students highly value the flexibility of using ChatGPT across devices and locations. These results are consistent with previous research (Alalwan et al., 2015; Kim and Kankanhalli, 2009), which highlights the importance of accessibility in technology adoption, particularly for modern learners balancing multiple responsibilities. Accessing ChatGPT anytime and anywhere enables students to integrate it seamlessly into their study routines, fostering continuous engagement. Similar findings were reported by Mercan et al. (2024) and Sisouvong and Pasanchay (2024), who noted that the convenience of mobile learning tools strongly influenced students' acceptance. This highlights that contextual and usage-related factors are increasingly relevant in AI adoption, justifying the inclusion of MC in the extended TAM framework.

Among the control variables, students' academic year had a negative influence on BU (coef. = -0.039, $p = 0.013$), indicating that more senior students might be less inclined to adopt new technologies like ChatGPT compared to their junior peers. This could be attributed to senior students relying on traditional learning methods or being less open to adopting newer tools. Based on Baidoo-Anu et al. (2024) and Pellas (2023), gender and frequency of use did not significantly affect BU, implying these factors are less influential in this context. The frequency of technology use in academic contexts does not affect the behavior of ChatGPT use, contrary to the study by Widodo and Akbar (2024). This result shows that senior students with experience using AI tools, such as ChatGPT, recognize their advantages and disadvantages, particularly in making students more dependent on technology. Hence, they decided to use ChatGPT less for their academic activities.

Overall, these findings confirm that while the core constructions of TAM, particularly PU, remain relevant, AI tools such as ChatGPT necessitate an expanded model that incorporates contextual variables like MC. Moreover, the evolving nature of student attitudes and the diverse usage patterns observed in recent global studies indicate that future models of technology adoption in education must address the dynamic interplay between functionality, trust, and access. The results offer a nuanced contribution to the literature by combining classical acceptance constructs with current usage patterns of generative AI in learning environments.

5.2. Theoretical implications

This study extends the existing literature on technology adoption by providing new insights into applying the TAM in the context of AI tools, such as ChatGPT. While TAM has traditionally emphasized perceived usefulness and perceived ease of use as primary drivers of technology adoption, this research highlights the critical role of mobility and convenience, a relatively underexplored factor in the model. The significant positive impact of MC on user behavior underscores the need to incorporate context-specific variables into TAM to better capture the dynamics of modern technology usage, particularly in educational environments.

Furthermore, this study provides empirical evidence that challenges conventional assumptions about perceived ease of use. The slight negative influence of PEOU on usage behavior suggests that familiarity with similar technologies can diminish its importance, shifting user focus toward practical benefits. This finding aligns with Venkatesh et al. (2003), who suggested that ease of use becomes less relevant as users gain experience with technology, but contrasts with studies that treat PEOU as universally significant (Maheshwari, 2024).

This research contributes to the growing body of knowledge on technology adoption in emerging markets by applying the TAM in a Vietnamese university context. The findings emphasize that while traditional TAM constructs remain relevant, additional factors, such as MC and demographic nuances, must be considered to fully understand user behavior in specific cultural and institutional settings. This study reaffirms the applicability of TAM while proposing extensions that can be tested in other educational and technological contexts.

Lastly, the study's findings regarding demographic variables, such as the academic year, offer new insights into how user characteristics impact technology adoption. Senior students' lower inclination to adopt ChatGPT suggests a potential resistance to change or a reliance on established learning habits, which warrants further investigation. These insights underscore the importance of tailoring technology adoption strategies to the specific needs and preferences of different user groups, thereby contributing to a more nuanced understanding of the TAM in diverse contexts.

5.3. Practical implications

The findings of this study provide valuable insights for educators, developers, and policymakers seeking to enhance the adoption and utilization of ChatGPT in educational settings.

The significant influence of perceived usefulness, mobility, and convenience on students' use behavior underscores the need to integrate ChatGPT into curricula and learning activities. Educators should emphasize the practical benefits of ChatGPT, including its ability to streamline research, enhance efficiency, and provide instant feedback. Additionally, training sessions could be organized to familiarize students with the tool's functionalities and demonstrate its applicability in various academic contexts. These initiatives can help overcome potential resistance among senior students who may be less inclined to adopt new technologies. To ensure effective and balanced use, students should be encouraged to treat ChatGPT as a supplementary tool rather than a replacement for independent thinking. They should verify their responses with credible sources and avoid over-reliance by actively engaging in the learning process. ChatGPT can become an asset in enhancing academic performance without compromising intellectual independence by fostering critical thinking and responsible use.

Developers should prioritize enhancing the accessibility and convenience of ChatGPT. Features such as offline functionality, integration with existing learning management systems, and enhanced language support can further increase its appeal. Addressing data security and privacy concerns is also crucial to building trust among users. Offering personalized recommendations and adaptive learning features based on user behavior could enhance engagement and satisfaction, making ChatGPT a more indispensable tool for students.

To promote widespread adoption, policymakers should support the integration of AI tools, such as ChatGPT, into national education strategies. Funding technology infrastructure and digital literacy programs can ensure equitable access for all students, particularly those in underprivileged areas. Policymakers could also collaborate with educational institutions to develop guidelines for the ethical and effective use of AI tools in learning environments. Students' concerns about the complexity and unfamiliarity of ChatGPT highlight the need for user-friendly design and clear onboarding processes. Developers and institutions should also collaborate to provide resources that address misconceptions and demonstrate the tool's reliability and effectiveness.

In addition to the above, integrating ChatGPT into institutional digital ecosystems, such as learning management systems (LMS), digital libraries, and assignment portals, can streamline access and encourage habitual use among students. Offering gamified tutorials or certification badges for AI literacy may further incentivize adoption. Moreover, establishing peer-led support networks or "AI learning ambassadors" within universities can promote collaborative exploration and reduce barriers for first-time users. These low-cost, high-impact initiatives can significantly enhance the scale and sustainability of ChatGPT adoption in educational environments.

By implementing these practical measures, stakeholders can maximize the potential of ChatGPT to transform learning experiences, making education more efficient, personalized, and accessible for students worldwide.

5.4. Limitations and future research

Although this study offers valuable insights into the adoption of ChatGPT in higher education settings, several limitations must be acknowledged.

First, while this study focused on perceived usefulness, perceived ease of use, mobility and convenience as primary factors, other variables may also influence the adoption of ChatGPT. Factors such as social influence, prior experience with AI tools, and cultural attitudes were not examined and could offer additional perspectives. Future research should consider integrating these factors into the analysis to provide a more comprehensive understanding of technology adoption.

Second, this research was conducted within a single institution in Vietnam. While Phenikaa University represents a diverse student body, the findings may not be fully generalized to other universities or regions. Expanding the study to include multiple institutions and geographical locations would enhance its generalizability and offer broader insights into ChatGPT adoption across different educational contexts.

Third, this study did not examine specific use cases of ChatGPT, such as its application in writing, coding, or collaborative learning tasks. Depending on students' academic needs and disciplines, each function may influence adoption differently. Future studies should investigate these use cases in greater depth to develop tailored strategies for promoting ChatGPT adoption across various fields.

Lastly, this study relied on cross-sectional data, which provide a snapshot of student behavior at a single point in time. Longitudinal studies tracking changes in adoption behavior over time could offer richer insights into how students adapt to and integrate ChatGPT into their learning routines.

By addressing these limitations, future research can build on the findings of this study to deepen our understanding of AI adoption in education and refine strategies for promoting effective and equitable use of ChatGPT and similar technologies.

6. Conclusion

This study investigated the factors influencing students' behavior of use of ChatGPT in educational settings, focusing on an extended Technology Acceptance Model. The research utilized quantitative methods to analyze data collected from university students in Vietnam. The findings revealed that perceived usefulness, mobility, and convenience significantly positively impact ChatGPT adoption, while perceived ease of use showed a slight negative influence. The academic year was also identified as a demographic factor affecting adoption patterns, with senior students being less inclined to use ChatGPT compared to their junior counterparts. These results offer valuable insights for educators, developers, and policymakers to facilitate the adoption of AI tools, such as ChatGPT. Practical recommendations include emphasizing the tool's tangible benefits, improving accessibility, and tailoring strategies to different user groups. Despite some limitations, this study makes a valuable contribution to the growing body of literature on the adoption of AI in education. It provides a foundation for future research to build upon these findings and explore ChatGPT's potential in various contexts.

List of abbreviations

AI	Artificial intelligence
TAM	Technology acceptance model
UTAUT	Unified theory of acceptance and use of technology
PU	Perceived usefulness
PEOU	Perceived ease of use
MC	Mobility and convenience
BU	Behavior of use
SEM	Structural equation modeling
EFA	Exploratory factor analysis
CFA	Confirmatory factor analysis
CR	Composite reliability
AVE	Average variance extracted
CFI	Comparative fit index
TLI	Tucker-Lewis index
SRMR	Standardized root mean square residual
RMSEA	Root mean squared error of approximation
KMO	Kaiser-Meyer-Olkin
ICT	Information and communication technology
CAGR	Compound annual growth rate
LMS	Learning management system

Compliance with ethical standards

Ethical considerations

This study was conducted in accordance with the ethical standards of Phenikaa University and international guidelines for research integrity. Informed consent was obtained from all participants prior to data collection. Participation was voluntary, responses were anonymous, and no personal identifying information was collected. All data were treated with strict confidentiality and used solely for academic purposes.

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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