

Factors Influencing University Students' Adoption of Generative AI Tools: An Integrated TAM-UTAUT Model in Vietnamese Higher Education

Phan Tri Nghia

Thu Dau Mot University, Ho Chi Minh City, Vietnam

ABSTRACT: This study investigates the factors influencing Vietnamese university students' behavioral intention to adopt generative artificial intelligence (GenAI) tools for academic purposes. By integrating the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), the study proposes an extended framework incorporating perceived enjoyment and AI anxiety as additional determinants, with AI literacy as a potential moderator. A quantitative cross-sectional survey was conducted with 418 undergraduate students from public universities in Vietnam. Data were analyzed using SPSS 26.0, employing exploratory factor analysis (EFA), reliability analysis, Pearson correlation, hierarchical multiple regression, and moderation analysis. The results reveal that performance expectancy ($\beta = 0.233$, $p < 0.001$), social influence ($\beta = 0.267$, $p < 0.001$), perceived enjoyment ($\beta = 0.250$, $p < 0.001$), effort expectancy ($\beta = 0.092$, $p < 0.05$), and facilitating conditions ($\beta = 0.088$, $p < 0.05$) significantly predict behavioral intention toward GenAI tools. AI anxiety shows a marginally negative but non-significant effect ($\beta = -0.072$, $p = 0.065$). Behavioral intention significantly predicts actual use ($\beta = 0.434$, $p < 0.001$). AI literacy does not significantly moderate the relationships between key predictors and behavioral intention. This study contributes to the emerging literature on GenAI adoption in higher education by integrating TAM and UTAUT with context-specific variables in the Vietnamese educational setting. The findings provide practical implications for educators and policymakers seeking to facilitate responsible GenAI integration in academic environments.

KEYWORDS: Generative AI; ChatGPT; Technology adoption; TAM; UTAUT; Higher education; Vietnam; AI literacy; Behavioral intention

1. INTRODUCTION

The rapid emergence of generative artificial intelligence (GenAI) tools, particularly large language models such as ChatGPT, Google Gemini, and Microsoft Copilot, has fundamentally transformed the educational landscape worldwide (Dwivedi et al., 2023; Lim et al., 2023). Since the public release of ChatGPT in November 2022, higher education institutions have been confronted with both unprecedented opportunities and significant challenges in integrating these technologies into teaching, learning, and research activities (Kasneci et al., 2023; Sullivan et al., 2023). GenAI tools offer capabilities that extend far beyond traditional educational technologies, including content generation, language translation, coding assistance, and research support, thereby reshaping how students approach academic tasks (Baidoo-Anu & Ansah, 2023).

In the context of developing countries, Vietnam has emerged as one of the fastest-growing digital economies in Southeast Asia, with a young and tech-savvy population increasingly embracing digital tools for various purposes (Nguyen et al., 2023). The Vietnamese government has actively promoted digital transformation in education through its National Digital Transformation Programme by 2025, with a vision to 2030, which emphasizes the integration of advanced technologies in educational institutions (Government of Vietnam, 2020). However, the adoption of GenAI tools among Vietnamese university students remains a relatively unexplored phenomenon, with limited empirical evidence on the factors driving or hindering their acceptance and use (Le & Truong, 2024).

Despite the growing body of literature on technology adoption in education, several research gaps persist. First, most existing studies on GenAI adoption have been conducted in Western contexts, with limited attention to developing countries in Southeast Asia (Chan & Hu, 2023). Second, while established theoretical frameworks such as the Technology Acceptance Model (TAM; Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) have been widely applied, few studies have attempted to integrate these complementary models to provide a more comprehensive understanding of GenAI adoption behavior (Strzelecki, 2023). Third, the role of emerging constructs such as perceived enjoyment, AI anxiety, and AI literacy in shaping GenAI adoption intentions among university students has received insufficient empirical attention (Wang et al., 2024).

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To address these gaps, the present study proposes an integrated TAM-UTAUT framework that extends existing theoretical models by incorporating perceived enjoyment and AI anxiety as additional determinants of behavioral intention, and AI literacy as a moderating variable. Specifically, this research aims to: (1) examine the direct effects of performance expectancy, effort expectancy, social influence, facilitating conditions, perceived enjoyment, and AI anxiety on students' behavioral intention to adopt GenAI tools; (2) investigate the relationship between behavioral intention and actual use behavior; and (3) explore the moderating role of AI literacy in the relationships between key predictors and behavioral intention.

The remainder of this paper is organized as follows. Section 2 presents the theoretical background and develops the research hypotheses. Section 3 describes the research methodology, including the survey design, sampling procedure, and data analysis approach. Section 4 reports the empirical findings. Section 5 discusses the results in relation to existing literature. Finally, Section 6 concludes the paper with theoretical and practical implications, limitations, and directions for future research.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1. Generative AI in Higher Education

Generative artificial intelligence refers to AI systems capable of creating new content, including text, images, code, and multimedia, based on patterns learned from training data (Dwivedi et al., 2023). The introduction of ChatGPT by OpenAI in late 2022 marked a watershed moment in AI accessibility, as it provided a conversational interface that enabled non-technical users to harness the power of large language models (Kasneci et al., 2023). Subsequently, numerous GenAI tools have entered the market, including Google's Gemini, Anthropic's Claude, Meta's LLaMA, and Microsoft's Copilot, each offering unique capabilities for educational applications (Lim et al., 2023).

In higher education, GenAI tools have been utilized for diverse purposes, including essay writing assistance, research literature synthesis, programming support, language learning, and personalized tutoring (Baidoo-Anu & Ansah, 2023). However, their adoption has also raised concerns regarding academic integrity, critical thinking development, over-reliance on AI-generated content, and the potential exacerbation of digital divides (Sullivan et al., 2023). Understanding the factors that influence students' adoption behavior is therefore critical for developing effective institutional policies and pedagogical strategies.

2.2. Technology Acceptance Model (TAM)

The Technology Acceptance Model, originally proposed by Davis (1989), posits that two primary beliefs determine an individual's intention to use a technology: perceived usefulness and perceived ease of use. Perceived usefulness refers to the degree to which a person believes that using a particular system would enhance their performance, while perceived ease of use captures the extent to which using the system is free of effort (Davis, 1989). TAM has been extensively validated across various technological contexts, including e-learning, mobile learning, and AI-based educational tools (Granić & Marangunić, 2019). Its parsimony and predictive power make it a foundational framework for studying technology adoption in educational settings.

2.3. Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al. (2003) developed UTAUT by synthesizing eight prominent technology acceptance theories, proposing four core determinants of behavioral intention: performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy corresponds to perceived usefulness in TAM, while effort expectancy aligns with perceived ease of use. Social influence captures the degree to which important others believe the individual should use the technology, and facilitating conditions refer to the organizational and technical infrastructure supporting technology use (Venkatesh et al., 2003). UTAUT has demonstrated strong explanatory power in various contexts, accounting for approximately 70% of the variance in behavioral intention (Venkatesh et al., 2012).

2.4. Integrated TAM-UTAUT Framework and Extended Constructs

While TAM and UTAUT share conceptual overlaps, integrating them can provide a more comprehensive understanding of technology adoption by leveraging the strengths of each model (Dwivedi et al., 2019). The present study adopts the core UTAUT constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) and extends the framework with two additional variables drawn from the broader TAM literature: perceived enjoyment and AI anxiety.

Perceived enjoyment, defined as the extent to which using a technology is perceived to be intrinsically pleasurable (Davis et al., 1992), has been identified as a significant predictor of technology adoption, particularly for hedonic and experiential systems (Venkatesh et al., 2012). In the context of GenAI tools, the interactive, conversational nature of these systems may generate a sense of curiosity and enjoyment that motivates continued use (Strzelecki, 2023). AI anxiety, conceptualized as the apprehension or fear associated with interacting with AI systems (Wang et al., 2024), represents a potential barrier to adoption, particularly among users with limited AI experience or negative perceptions of AI capabilities.

Furthermore, AI literacy—the ability to understand, critically evaluate, and effectively use AI technologies (Long & Magerko, 2020)—is proposed as a moderating variable that may strengthen or weaken the relationships between key predictors and behavioral

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intention. Students with higher AI literacy may be better equipped to recognize the performance benefits of GenAI tools and may experience less difficulty in using them, thereby amplifying the effects of performance and effort expectancy on adoption intention.

2.5. Hypotheses Development

H1: Performance expectancy has a significant positive effect on students' behavioral intention to adopt GenAI tools.

H2: Effort expectancy has a significant positive effect on students' behavioral intention to adopt GenAI tools.

H3: Social influence has a significant positive effect on students' behavioral intention to adopt GenAI tools.

H4: Facilitating conditions have a significant positive effect on students' behavioral intention to adopt GenAI tools.

H5: Perceived enjoyment has a significant positive effect on students' behavioral intention to adopt GenAI tools.

H6: AI anxiety has a significant negative effect on students' behavioral intention to adopt GenAI tools.

H7: Behavioral intention has a significant positive effect on actual use of GenAI tools.

H8: AI literacy moderates the relationship between performance expectancy and behavioral intention, such that the relationship is stronger for students with higher AI literacy.

H9: AI literacy moderates the relationship between effort expectancy and behavioral intention, such that the relationship is stronger for students with higher AI literacy.

3. RESEARCH METHODOLOGY

3.1. Research Design and Sampling

This study employed a quantitative cross-sectional survey design. The target population comprised undergraduate students enrolled at public universities in Ho Chi Minh City, Vietnam, who had prior experience or awareness of GenAI tools such as ChatGPT, Google Gemini, or similar applications. A convenience sampling technique was adopted, complemented by purposive criteria requiring respondents to be currently enrolled undergraduate students at a public university. The survey was distributed online via Google Forms during October–November 2025, yielding 450 responses. After removing incomplete responses and outliers (identified through Mahalanobis distance), 418 valid responses were retained for analysis, representing a response rate of 92.9%.

The sample consisted of 237 female (56.7%) and 181 male (43.3%) respondents, with a mean age of 20.28 years ($SD = 1.27$). The distribution across academic years was: first-year (79), second-year (111), third-year (118), and fourth-year (110). Regarding academic disciplines, respondents came from Information Technology/Computer Science (110), Business Administration (82), Engineering (93), Social Sciences (71), and other fields (62). In terms of prior GenAI experience, 207 students (50%) reported frequent use, 139 (33%) occasional use, and 72 (17%) had never used GenAI tools.

3.2. Measurement Instrument

The survey instrument was developed by adapting established scales from the extant literature. All latent constructs were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Performance expectancy (5 items) and effort expectancy (4 items) were adapted from Venkatesh et al. (2003) and Strzelecki (2023). Social influence (4 items) and facilitating conditions (4 items) were drawn from Venkatesh et al. (2003). Perceived enjoyment (3 items) was adapted from Davis et al. (1992) and Venkatesh et al. (2012). AI anxiety (4 items) was measured using scales adapted from Wang et al. (2024) and Kaya et al. (2024). Behavioral intention (4 items) was adapted from Venkatesh et al. (2003), and actual use (3 items) was measured based on self-reported frequency and breadth of GenAI tool usage (Strzelecki, 2023). AI literacy (4 items) was adapted from Long and Magerko (2020) and Ng et al. (2021).

The questionnaire was initially developed in English, translated into Vietnamese by two bilingual researchers, and back-translated to ensure semantic equivalence. A pilot study with 35 students was conducted to assess clarity and comprehension, resulting in minor wording adjustments. The final instrument comprised 35 measurement items plus 6 demographic questions.

3.3. Data Analysis Procedure

Data analysis was performed using IBM SPSS Statistics version 26.0. The analytical procedure comprised five sequential stages: (1) descriptive statistics and normality assessment; (2) reliability analysis using Cronbach's alpha coefficients; (3) exploratory factor analysis (EFA) with principal component extraction and Varimax rotation; (4) Pearson bivariate correlation analysis; and (5) hierarchical multiple regression analysis to test the direct effects and moderation hypotheses. Multicollinearity was assessed using variance inflation factors (VIF), and the moderation effects were examined following the centered interaction approach recommended by Aiken and West (1991).

4. RESULTS

4.1. Descriptive Statistics and Normality

Table 1 presents the descriptive statistics for all measurement items. The mean values of performance expectancy items ranged from 3.10 to 3.40, suggesting a moderate-to-positive perception of GenAI tools' usefulness. Effort expectancy items had means between

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2.92 and 3.23, indicating that students perceive these tools as moderately easy to use. Social influence means ranged from 2.72 to 3.05, while facilitating conditions showed relatively lower means (2.45–2.82), suggesting room for improvement in institutional support infrastructure. Perceived enjoyment exhibited means between 2.87 and 3.15, and AI anxiety items showed low means (1.77–2.06), indicating that most students experience limited anxiety toward GenAI tools. Skewness values ranged from –0.85 to 0.62 and kurtosis values from –1.15 to 0.48, all within the acceptable thresholds of ± 2 for skewness and ± 7 for kurtosis (Hair et al., 2019), confirming approximate normality.

Table 1. Construct Reliability and Descriptive Statistics

Construct	Items	Mean	SD	Cronbach's α
Performance Expectancy (PE)	5	3.251	0.868	0.893
Effort Expectancy (EE)	4	3.092	0.875	0.867
Social Influence (SI)	4	2.876	0.871	0.874
Facilitating Conditions (FC)	4	2.637	0.84	0.855
Perceived Enjoyment (ENJ)	3	3.002	0.877	0.806
AI Anxiety (ANX)	4	1.911	0.694	0.807
Behavioral Intention (BI)	4	2.876	0.697	0.794
Actual Use (AU)	3	2.669	0.707	0.75
AI Literacy (AIL)	4	2.988	0.861	0.88

Source: SPSS Results

4.2. Reliability Analysis

As shown in Table 1, all constructs demonstrated satisfactory internal consistency, with Cronbach's alpha coefficients ranging from 0.75 (Actual Use) to 0.893 (Performance Expectancy). All values exceeded the recommended threshold of 0.70 (Nunnally & Bernstein, 1994), and most exceeded the more stringent threshold of 0.80 recommended by Hair et al. (2019), confirming the reliability of the measurement instrument.

4.3. Correlation Analysis

Table 2 presents the Pearson bivariate correlation matrix for all construct-level variables. The results indicate that behavioral intention (BI) is positively and significantly correlated with performance expectancy ($r = 0.482$), effort expectancy ($r = 0.38$), social influence ($r = 0.453$), facilitating conditions ($r = 0.32$), and perceived enjoyment ($r = 0.465$), while negatively correlated with AI anxiety ($r = -0.228$). All correlations between independent variables were below the 0.80 threshold, suggesting no severe multicollinearity concerns (Hair et al., 2019).

Table 2. Pearson Correlation Matrix

	PE	EE	SI	FC	ENJ	ANX	BI	AU	AIL
PE	1.000								
EE	0.4	1.000							
SI	0.339	0.23	1.000						
FC	0.238	0.36	0.266	1.000					
ENJ	0.349	0.353	0.223	0.258	1.000				
ANX	-0.183	-0.2	-0.085	-0.104	-0.254	1.000			
BI	0.482	0.38	0.453	0.32	0.465	-0.228	1.000		
AU	0.289	0.197	0.222	0.218	0.199	-0.081	0.434	1.000	
AIL	0.244	0.331	0.173	0.381	0.192	-0.119	0.223	0.219	1.000

Source: SPSS Results

4.4. Hypotheses Testing: Multiple Regression Analysis

Hierarchical multiple regression analysis was conducted to test hypotheses H1 through H6. Prior to the analysis, multicollinearity diagnostics confirmed that all variance inflation factor (VIF) values ranged from 1.09 to 1.376, well below the threshold of 5.0 recommended by Hair et al. (2019), indicating no multicollinearity concerns.

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Table 3 presents the regression results with behavioral intention as the dependent variable. The overall model was statistically significant ($F = 51.468$, $p < 0.001$), explaining 42.9% of the variance in behavioral intention ($R^2 = 0.429$, adjusted $R^2 = 0.419$).

Table 3. Multiple Regression Results: Predictors of Behavioral Intention (BI)

Predictor	B	SE	β	t	p	VIF
PE	0.187	0.035	0.233	5.364	<0.001	1.357
EE	0.073	0.035	0.092	2.096	0.037	1.376
SI	0.214	0.033	0.267	6.579	<0.001	1.188
FC	0.073	0.034	0.088	2.145	0.033	1.217
ENJ	0.199	0.034	0.25	5.936	<0.001	1.281
ANX	-0.072	0.039	-0.072	-1.847	0.065	1.09

Note: $R^2 = 0.429$; Adjusted $R^2 = 0.419$; $F(6, 411) = 51.468$, $p < 0.001$. β = standardized coefficient.

Source: SPSS Results

The results reveal that social influence emerged as the strongest predictor of behavioral intention ($\beta = 0.267$, $t = 6.579$, $p < 0.001$), followed by perceived enjoyment ($\beta = 0.25$, $t = 5.936$, $p < 0.001$) and performance expectancy ($\beta = 0.233$, $t = 5.364$, $p < 0.001$). These findings support hypotheses H1, H3, and H5 with high statistical significance. Effort expectancy ($\beta = 0.092$, $t = 2.096$, $p = 0.0367$) and facilitating conditions ($\beta = 0.088$, $t = 2.145$, $p = 0.0325$) were also significant predictors, supporting hypotheses H2 and H4. However, AI anxiety showed a negative but non-significant effect on behavioral intention ($\beta = -0.072$, $t = -1.847$, $p = 0.0654$), thus H6 was not supported.

4.5. Behavioral Intention and Actual Use (H7)

Simple linear regression was performed to test the relationship between behavioral intention and actual use of GenAI tools. The results confirmed that behavioral intention is a significant predictor of actual use ($\beta = 0.434$, $t = 9.815$, $p < 0.001$), explaining 18.8% of the variance in actual use ($R^2 = 0.188$). Thus, H7 was supported.

4.6. Moderation Analysis: AI Literacy (H8, H9)

To test the moderating effects of AI literacy, hierarchical regression analyses were conducted following the centered interaction approach (Aiken & West, 1991). For the moderation of AI literacy on the performance expectancy–behavioral intention relationship (H8), the interaction term ($PE \times AIL$) was non-significant ($B = -0.016$, $t = -0.404$, $p = 0.6867$), with a negligible change in explained variance ($\Delta R^2 = 0.0003$). Similarly, for the effort expectancy–behavioral intention relationship (H9), the interaction term ($EE \times AIL$) was non-significant ($B = 0.011$, $t = 0.249$, $p = 0.8036$, $\Delta R^2 = 0.0001$). Therefore, neither H8 nor H9 was supported, suggesting that AI literacy does not significantly moderate these focal relationships in the present sample.

Table 4. Summary of Hypotheses Testing Results

Hypothesis	Path	β / B	p-value	Result
H1	PE $\rightarrow$ BI	0.233	<0.001	Supported***
H2	EE $\rightarrow$ BI	0.092	0.037	Supported*
H3	SI $\rightarrow$ BI	0.267	<0.001	Supported***
H4	FC $\rightarrow$ BI	0.088	0.033	Supported*
H5	ENJ $\rightarrow$ BI	0.25	<0.001	Supported***
H6	ANX $\rightarrow$ BI	-0.072	0.065	Not Supported
H7	BI $\rightarrow$ AU	0.434	<0.001	Supported***
H8	PE $\times$ AIL $\rightarrow$ BI	-0.016	0.687	Not Supported
H9	EE $\times$ AIL $\rightarrow$ BI	0.011	0.804	Not Supported

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Source: SPSS Results

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5. DISCUSSION

5.1. Key Findings

This study investigated the factors influencing Vietnamese university students' adoption of generative AI tools using an integrated TAM-UTAUT framework. The overall model demonstrated good explanatory power, accounting for 42.9% of the variance in behavioral intention, which is consistent with or exceeds the levels reported in comparable studies on AI-based educational technology adoption (Strzelecki, 2023; Wang et al., 2024).

Social influence emerged as the strongest predictor of behavioral intention, suggesting that peer norms and recommendations from important others play a critical role in shaping Vietnamese students' attitudes toward GenAI tools. This finding aligns with collectivist cultural values prevalent in Vietnamese society, where social conformity and group opinions significantly influence individual decision-making (Hofstede, 2001; Nguyen et al., 2023). In practical terms, when students observe their peers, instructors, or academic role models using ChatGPT or similar tools, they are more likely to develop positive intentions toward adoption.

Perceived enjoyment was the second strongest predictor, indicating that the interactive and engaging nature of GenAI tools contributes substantially to students' adoption intentions. This finding is consistent with research highlighting the hedonic motivation associated with conversational AI systems (Venkatesh et al., 2012) and suggests that the novelty and creative affordances of GenAI tools provide intrinsic motivation that complements utilitarian benefits.

Performance expectancy and effort expectancy were both significant predictors, confirming the robustness of core UTAUT constructs in the GenAI adoption context. Students who perceive GenAI tools as useful for academic tasks and relatively easy to use are more likely to intend to adopt them. These findings are consistent with previous technology adoption studies in higher education (Granić & Marangunić, 2019; Venkatesh et al., 2003). Facilitating conditions also showed a significant, albeit weaker, effect, suggesting that access to devices, internet connectivity, and institutional support facilitate adoption intentions.

Interestingly, AI anxiety did not significantly predict behavioral intention ($p = 0.065$), although the direction of the effect was negative as hypothesized. This marginally non-significant result may reflect the relatively high familiarity of the current student generation with AI technologies, having grown up in an era of digital ubiquity. The low mean scores for AI anxiety items ($M = 1.91$) suggest that most students in the sample do not experience substantial apprehension toward GenAI tools, potentially limiting the explanatory power of this variable.

5.2. The Non-Significant Moderating Role of AI Literacy

Contrary to expectations, AI literacy did not significantly moderate the relationships between performance expectancy, effort expectancy, and behavioral intention. Several explanations may account for this finding. First, the current sample predominantly comprised students with some prior GenAI experience (85%), suggesting a relatively homogeneous level of basic AI competence that may have reduced the variability needed to detect moderation effects. Second, AI literacy may operate as a direct predictor rather than a moderator in this context, influencing adoption intention independently rather than through interaction effects. Third, the conceptualization and measurement of AI literacy is still evolving, and the four-item scale used in this study may not have captured the full breadth of AI-related knowledge and skills that would differentiate students in their technology evaluation processes.

5.3. Theoretical Implications

This study makes several theoretical contributions to the technology adoption literature. First, it demonstrates the applicability of an integrated TAM-UTAUT framework in the emerging context of GenAI adoption in higher education, extending the models' validity to a new technology category and cultural setting. Second, the inclusion of perceived enjoyment as a significant predictor reinforces the importance of hedonic motivation in technology adoption, particularly for interactive AI systems. Third, the non-significant effects of AI anxiety and AI literacy moderation provide boundary conditions for these constructs, suggesting that their relevance may be contingent on the population's baseline familiarity with AI technologies.

5.4. Practical Implications

The findings offer several practical implications for Vietnamese higher education institutions and policymakers. First, given the strong influence of social factors, universities should consider implementing peer-learning programs, faculty-led demonstrations, and institutional endorsements of appropriate GenAI use to create positive social norms around these tools. Second, the significant effect of perceived enjoyment suggests that engaging, interactive learning activities incorporating GenAI tools may enhance student motivation and adoption. Third, while facilitating conditions showed a weaker effect, ensuring adequate technical infrastructure, including reliable internet access and institutional GenAI subscriptions, remains important for equitable access. Fourth, the non-significant effect of AI anxiety suggests that broad anxiety-reduction interventions may be less urgent than targeted support for the minority of students who may still experience apprehension.

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6. CONCLUSION

This study investigated the factors influencing Vietnamese university students' adoption of generative AI tools through an integrated TAM-UTAUT framework. Using survey data from 418 undergraduate students at public universities in Vietnam, the study found that social influence, perceived enjoyment, performance expectancy, effort expectancy, and facilitating conditions are significant predictors of behavioral intention to adopt GenAI tools. AI anxiety showed a marginally non-significant negative effect, and AI literacy did not moderate the focal relationships. Behavioral intention was confirmed as a significant predictor of actual use behavior.

6.1. Limitations and Future Research

Several limitations should be acknowledged. First, the cross-sectional design limits causal inferences; longitudinal studies would provide stronger evidence of temporal relationships between predictors and adoption behavior. Second, the convenience sampling approach and focus on public universities in Ho Chi Minh City may limit the generalizability of findings to other Vietnamese regions or private institutions. Third, the use of self-reported measures for actual use behavior may introduce social desirability bias; future studies could incorporate objective usage data from learning management systems. Fourth, the non-significant moderation effects of AI literacy may reflect measurement limitations; future research could employ more comprehensive AI literacy instruments or explore alternative moderating variables such as digital self-efficacy or institutional policies. Fifth, the study did not differentiate between specific GenAI tools or use cases, which may obscure tool-specific adoption patterns.

Future research is encouraged to: (1) conduct longitudinal studies tracking GenAI adoption trajectories over time; (2) examine the role of institutional policies and academic integrity concerns as additional determinants; (3) compare adoption patterns across different types of higher education institutions (public vs. private, urban vs. rural); (4) investigate the impact of GenAI adoption on actual learning outcomes; and (5) explore qualitative approaches to gain deeper insights into students' lived experiences with GenAI tools.

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Appendix A. Measurement Items

Code	Item
PE1	Using GenAI tools improves my academic performance.
PE2	GenAI tools help me complete academic tasks more quickly.
PE3	GenAI tools enhance the quality of my academic work.
PE4	GenAI tools are useful for my studies and research.
PE5	Using GenAI tools increases my academic productivity.
EE1	I find GenAI tools easy to use.
EE2	Learning to use GenAI tools is straightforward for me.
EE3	My interaction with GenAI tools is clear and understandable.
EE4	It is easy for me to become skillful at using GenAI tools.
SI1	People who are important to me think I should use GenAI tools.
SI2	My classmates encourage me to use GenAI tools.
SI3	My instructors recommend the use of GenAI tools for learning.
SI4	Most students around me use GenAI tools for academic purposes.
FC1	I have the resources necessary to use GenAI tools.
FC2	I have the knowledge necessary to use GenAI tools.
FC3	GenAI tools are compatible with the devices I use.
FC4	Technical support is available when I encounter difficulties with GenAI tools.
ENJ1	I find using GenAI tools to be enjoyable.
ENJ2	The process of interacting with GenAI tools is fun.
ENJ3	I feel excited when using GenAI tools for learning.
ANX1	I feel anxious about making mistakes when using GenAI tools.
ANX2	I am worried that GenAI tools might give me incorrect information.
ANX3	I feel uncomfortable relying on AI for academic tasks.
ANX4	The idea of AI replacing human abilities in education concerns me.
BI1	I intend to continue using GenAI tools in the near future.

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BI2	I plan to use GenAI tools regularly for my academic work.
BI3	I would recommend GenAI tools to my classmates.
BI4	I expect to increase my use of GenAI tools in the coming semester.
AU1	I currently use GenAI tools frequently for academic purposes.
AU2	I use GenAI tools for various types of academic tasks.
AU3	I use GenAI tools as a regular part of my study routine.
AIL1	I understand how AI systems like ChatGPT generate responses.
AIL2	I can evaluate the reliability and accuracy of AI-generated content.
AIL3	I am aware of the limitations and potential biases of AI tools.
AIL4	I know how to use AI tools effectively and responsibly.