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Factors influencing students' intention to use Artificial Intelligence (AI) for learning and research in Ho Chi Minh City

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Abstract Within the context of the Fourth Industrial Revolution, the integration of artificial intelligence (AI) into higher education has become inevitable. AI tools are used by students to increase the efficiency of learning and research; however, acceptance levels vary across individuals. Among university students, usage is still mostly informal and lacks official recognition or adequate instruction, especially in developing countries. There has been limited research investigating the determinants that lead to students' intention to adopt AI in learning and research, especially within emerging economies such as Vietnam. On the basis of this gap, this study identifies and measures factors influencing the intention to use AI for learning and research among students in Ho Chi Minh City, drawing on an extended UTAUT2 model. With the extension of UTAUT2, the proposed model involves the integration of core acceptance factors with individual-level extensions. Data were collected from 258 students via an online survey and analyzed with SPSS 26. The linear regression results indicate that performance expectancy, perceived interactivity, and facilitating conditions positively and strongly predict intention to use, whereas privacy concerns exert a significant negative effeclt. The three strongest positive predictors are performance expectancy, perceived interactivity, and facilitating conditions. The findings help clarify the drivers of and barriers to AI use in higher education. Following these findings, this study has practical implications for universities, instructors, and technology developers to improve the effectiveness of AI integration in higher education. These findings are intended to reinforce learning and research outcomes and support the development of effective AI integration strategies in Vietnam's higher education system, promoting intelligence and sustainability.

Keywords: intention to adopt, Artifical Intelligence in education, higher education, technology acceptance theories

1. Introduction

Artificial intelligence (AI) has emerged as a key driver of innovation across sectors, particularly in education. Recent studies have shown that a large proportion of students in developed countries (e.g., the United States, the United Kingdom, and Australia) use AI tools such as ChatGPT, Gemini AI, or Copilot to support learning and research (Zawacki-Richter et al., 2019). In developing contexts such as Vietnam, although large-scale institutional integration of AI in higher education remains limited, student-level adoption is expanding rapidly. Recent survey-based studies in Southeast Asia report that more than half of university students have experiment with or regularly used AI tools for academic purposes, driven by advances in natural language processing, ease of use, and multifunctional capabilities, including information retrieval, question answering, data analysis, and drafting support (Tlili et al., 2023).

While AI offers opportunities, effective integration into education remains challenging. Factors such as performance expectancy, perceived ease of use, facilitating conditions, and privacy concerns may strongly shape students' intention to use AI. Given the need to process complex information and engage in analytical thinking, students stand to benefit from AI support; however, acceptance is influenced not only by technical features but also by psychological, social, and environmental determinants. These determinants merit careful examination to clarify the drivers of and barriers to AI use in higher education.

Despite increasing attention being given to the adoption of artificial intelligence (AI) tools in higher education, such adoption by university students is still considered informal and unoficially yet insufficiently instructed, especially within developing contexts. Existing literature demonstrates that while AI applications in higher education are escalating rapidly, institutional policies and educational guidance are still under-developed, leading to the lack of support for student usage (Crompton & Burke, 2023).Previous studies have shown that AI offers remarkable opportunities yet challenges related to learning and research and that there are related controversial issues, such as research ethics and academic integrity (Kasneci et al., 2023; Tlili et al., 2023). In addition, current AI applications in edutation and research have been dominated by studies in

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developed nations, leaving limited empirical evidence on the adoption of AI technologies by students in emerging economies (Zawacki-Richter et al., 2019).

This gap is especially relevant in Vietnam, where student use of generative AI is significantly increasing despite limited institutional integration. Distinctive features related to educational culture, technological infrastructure, and institutional support mechanisms may affect students' perceptions of AI usefulness, ease of use, and potential risks. These perceptions are considered as central factors in technology acceptance research, as proposed in the Technology Acceptance Model (Davis, 1989). Zawacki-Richter et al. (2019) raised the call for more context-sensitive and theory-driven research for a better understanding of AI adoption in higher education. Responding to this call, the present study investigates the factors influencing students' intention to use AI for learning and research in Ho Chi Minh City, which can provide empirical evidence informing sustainable and responsible AI integration in Vietnamese higher education. The main focus of the study is on AI-based learning management systems.

This study analyzes the factors influencing students' intention to use AI for learning and research in Ho Chi Minh City. Building on technology acceptance theories (UTAUT2 and TAM), we examine performance expectancy, effort expectancy, perceived interactivity, facilitating conditions, social influence, personal innovativeness, and privacy concerns. The goal is to provide a comprehensive view of students' needs, attitudes, and behaviors toward AI and to offer actionable recommendations for institutions, instructors, and technology developers. The findings aim to enhance learning and research quality and inform strategies for AI application in Vietnamese higher education toward an intelligent, sustainable system.

2. Theoretical Background

2.1. Artificial intelligence: Definition and scope

AI is a field of computer science focused on developing systems capable of performing tasks that require human intelligence—such as learning, reasoning, language understanding, and problem solving (Russell & Norvig, 2020). McCarthy (2007) emphasized that AI not only simulates human behavior but also optimizes performance by leveraging large-scale data processing and learning from experience (Kaplan & Haenlein, 2019). In education, AI has enabled virtual assistants, personalized content delivery, and learning analytics, thereby improving learning and research outcomes (Holmes et al., 2019). AI in education is applied as intelligent systems designed to support, enhance, and speed up human cognitive processes (Luckin et al., 2016). Conversational AI tools (e.g., ChatGPT, Gemini AI) allow students to retrieve information rapidly, resolve queries, draft text, and even support complex data analysis.

2.2. Behavioral intention to use technology

Behavioral intention refers to an individual's readiness to employ a system or technological tool to accomplish specific tasks (Davis, 1989). In the theory of planned behavior, intention mediates the attitude–behavior link and predicts actual use (Ajzen, 1991). In UTAUT, intention is shaped by performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). In educational contexts, students' intention to use AI reflects their acceptance of and confidence in AI tools to improve learning and research outcomes. Beyond technical affordances, intention is also shaped by psychological, social, and environmental factors—for example, anticipated academic benefits, privacy concerns, and peer or instructor influence.

2.3. Technology acceptance models

The Technology Acceptance Model (TAM) (Davis, 1989) is a widely used framework for explaining technology use on the basis of perceived usefulness and perceived ease of use. Although the TAM has been applied extensively in educational technology—including AI tools—it downplays social and contextual factors. UTAUT (Venkatesh et al., 2003) and the extended UTAUT2 (Venkatesh et al., 2012) address this by incorporating performance expectancy, effort expectancy, social influence, facilitating conditions, habits, hedonic motivation, and price/value. UTAUT2 is particularly suited to studying AI adoption in education because it links behavioral and contextual determinants. For example, performance expectancy captures beliefs that AI improves academic results, whereas social influence reflects peer and instructor pressures or encouragement. This study adopts UTAUT2 as the core framework and extends it with perceived interactivity and privacy concerns to better capture the characteristics of conversational AI.

2.4. Literature Review

This section synthesizes prior work on students' intention to use AI (particularly conversational AI) for learning and research, integrating domestic and international evidence from the UTAUT2/TAM lens. Rather than listing studies, we thematically compare determinants, contextualize Vietnamese findings, note methodological patterns, and surface gaps that motivate the present model.

2.4.1. Thematic Synthesis of Determinants

2.4.1.1. Performance and Effort Expectancy

Across contexts, performance expectancy (PE) consistently predicts the intention to use AI: students adopt AI when they perceive tangible gains in learning efficiency, output quality, and time savings (Foroughi et al., 2023; Camilleri, 2024). The evidence in Vietnam is mixed: one single-institution study revealed that PE is significant alongside facilitating conditions (Nguyen & Nguyen, 2024), whereas a multicampus sample reported nonsignificance for both PE and effort expectancy (EE), suggesting that students may prioritize social/experiential attributes over pure utility and ease (Nguyen et al., 2024). In sum, PE is generally salient, but its magnitude may vary with the maturity of AI use and institutional norms; EE tends to be a secondary, enabling factor rather than a primary driver.

2.4.1.2. Social Influence and Habit

Social influence (SI) is often a consequential, context-dependent driver. Global evidence indicates positive effects (Strzelecki, 2023), whereas in Vietnam, SI ranges from nonsignificant (Nguyen & Nguyen, 2024) to significant (Nguyen et al., 2024). This divergence suggests that institutional messaging and peer norms can meaningfully modulate adoption trajectories. Relatedly, habit emerged as a strong predictor in the Danang study (Nguyen et al., 2024), echoing international findings that repeated, low-friction use cements intention (Strzelecki, 2023).

2.4.1.3. Facilitating Conditions

Facilitating conditions (FCs)—infrastructure, access, and support—have robust positive effects in both Vietnamese (Nguyen & Nguyen, 2024; Nguyen et al., 2024) and international contexts (Camilleri, 2024). This underscores the centrality of institutional investments (e.g., connectivity, licenses, help desks) for sustained adoption in higher education.

2.4.1.4. Perceived Interactivity

Emerging work emphasizes perceived interactivity (PI)—the responsiveness, contextuality, and conversational "naturalness" of AI—as a distinctive driver of chat-based tools (Tiwari et al., 2024; Camilleri, 2024). Domestic evidence (Nguyen et al., 2024) aligns, indicating that interaction quality can rival or surpass traditional TAM/UTAUT2 antecedents when the technology is dialogic and adaptive.

2.4.1.5. Privacy concerns

Across settings, privacy concerns (PCs) reliably deter intention (Malhotra et al., 2004; Strzelecki, 2023). Prior studies in information systems have similarly indicated that perceived privacy risks negatively affect users' trust and technology acceptance (Malhotra et al., 2004; Smith et al., 2011). In student populations that handle academic artifacts (notes, drafts, datasets), apprehensions about logging, retention, and data leakage appear particularly salient, positioning privacy safeguards as necessary complements to adoption initiatives.

2.4.1.6. Personal Innovativeness

Personal innovativeness (PII) generally contributes positively but modestly (Agarwal & Prasad, 1998; Nguyen et al., 2024). Individuals having higher levels of personal innovativeness usually tend to adapt with new technologies more rapidly and reveal early uptake behaviors (Yi et al., 2006). It helps explain early uptake and experimentation yet rarely substitutes for institutional and experiential factors (FC, PI).

2.4.1.7. Contextual Insights: Vietnam vs. *International*

Vietnamese studies reveal stronger effects from experiential and structural support (PIs, FCs), with PEs sometimes attenuated when students are early in their AI learning curve or when usage remains exploratory (Nguyen et al., 2024). Internationally, PE and SI/habit often play relatively large roles (Strzelecki, 2023; Foroughi et al., 2023; Camilleri, 2024). These differences likely reflect institutional readiness, guidance, and normalization of AI practices across campuses.

2.4.1.8. Methodological notes

Most studies deploy cross-sectional surveys with Likert-type scales adapted from TAM/UTAUT2 (Davis, 1989; Venkatesh et al., 2012). Domestic samples range from single-institution (≈200–400 respondents) to multi-institution (≈300+) samples and are analyzed via reliability checks, EFA/CFA or EFA+regression. International studies span larger, more heterogeneous samples (e.g., >3,000) (Strzelecki, 2023). While adequate for explanatory modeling, cross-sectional designs limit causal inference and the observation of habit formation and longitudinal change.

2.4.2. Gaps and Rationale for the Present Model

1. Conversational quality as a core determinant. Classical UTAUT2 underweights dialogic attributes; evidence supports incorporating perceived interactivity (PI) as a first-order predictor in chat-AI contexts (Camilleri, 2024).
2. Privacy as a Behavioral Friction. Privacy risk demonstrably suppresses intention (Strzelecki, 2023), warranting the explicit inclusion of privacy concerns (PCs) alongside enablers.
3. Institutional heterogeneity. Variations in FC and SI effects across Vietnamese universities suggest institutional moderation; capturing infrastructure and guidance is critical.
4. From Lists to Mechanisms. Beyond documenting significant factors, there is a need to articulate how FC and PI amplify PE (e.g., better interactions → clearer learning gains) and how PC dampens PE/SI effects—motivating an extended model that tests these pathways.

2.4.3. Comparative Summary of Representative Studies

2.4.3.1. Synthesis

Table 1 presents a comparative summary of representative studies. Taken together, prior research supports an extended UTAUT2 that elevates perceived interactivity and privacy concerns alongside classic determinants (PE, EE, FC, SI, PII). In Vietnamese higher education, FC and PI emerge as especially actionable levers—improving access/support and the quality of human-AI dialog—while privacy remains the most persistent barrier. These insights directly inform the present study's hypothesized model (Figure 1) and variable selection.

Table 1 Comparative Summary of Representative Studies.

Study	Context	Model	Key Predictors (+/−)	Notable Notes
Nguyen et al. (2024)	VN, multicampus, n≈300	UTAUT2-extended	FC(+), SI(+), Habit(+), PII(+), PI(+), PC(−); PE/EE ns	Highlights PI; privacy deters; early-stage adoption dynamics
Nguyen & Nguyen (2024)	VN, single university, n≈200–400	UTAUT	PE(+), FC(+); EE/SI ns	PE regains salience with localized support
Strzelecki (2023)	Global, 100 countries, n>3,000	UTAUT2-extended	PE(+), SI(+), Habit(+), PII(+); PC(−)	Research-leaning sample; strong norms/habit
Foroughi et al. (2023)	Malaysia, students	TAM	PE(+), EE(+), Hedonic(+), Value(+)	Cultural/infra differences vs. VN
Camilleri (2024)	Students, multisite	UTAUT2-extended	PI(+), PE(+), FC(+), Habit(+)	Elevates interactivity as a driver

2.5. Research Hypotheses

2.5.1. Performance expectancy

Performance expectancy is the degree to which students believe that using AI will improve learning and research effectiveness (Venkatesh et al., 2003). In education, it relates to AI's ability to provide accurate information, accelerate problem solving, and enhance the quality of assignments and research. Prior studies (Foroughi et al., 2023) suggest a strong link between performance expectancy and the intention to use AI tools.

H1 (+): Performance expectancy positively affects students' intention to use AI for learning and research.

2.5.2. Effort expectancy

Effort expectancy refers to the perceived ease of using AI (Davis, 1989). It encompasses user-friendly interfaces, clear guidance, and minimal technical barriers. TAM and UTAUT posit that ease of use is particularly important for users with limited technological experience. Camilleri (2024) emphasized that simple, streamlined experiences increase AI adoption.

H2 (+): Effort expectancy positively affects students' intention to use AI for learning and research.

2.5.3. Facilitating conditions

Facilitating conditions denote the extent to which students believe that adequate resources and support (e.g., stable internet, suitable devices, institutional guidance) are available (Venkatesh et al., 2003). In universities, these conditions are pivotal, especially when frequent access to AI is needed. Evidence from the University of Danang shows a significant positive effect ($\beta = 0.25$) on the intention to use ChatGPT (Nguyen et al., 2024).

H3 (+): Facilitating conditions positively affect students' intention to use AI for learning and research.

2.5.4. Social influence

Social influence is the degree to which students perceive encouragement or pressure from significant others (peers, instructors, family) to use AI (Venkatesh et al., 2003). In higher education, peer norms and instructor recommendations can shape attitudes toward emerging technologies. Strzelecki (2023) reported a positive effect of social influence on the intention to use ChatGPT for academic writing.

H4 (+): Social influence positively affects students' intention to use AI for learning and research.

2.5.5. Perceived interactivity

Perceived interactivity captures the natural, effective, and engaging quality of human–AI communication (Camilleri, 2024), including context-appropriate responses, prompt feedback, and a conversational feel. Personalized and context-sensitive responses can strengthen student engagement.

H5 (+): Perceived interactivity positively affects students' intention to use AI for learning and research.

2.5.6. Privacy concerns

Privacy concerns reflect students' concerns about the protection of personal and academic data when they use AI (Strzelecki, 2023). Given AI's data-intensive nature, students may fear misuse or leakage of information. Evidence from the University of Danang indicates a negative effect ($\beta = -0.15$) on the intention to use ChatGPT (Nguyen et al., 2024).

H6 (−): Privacy concerns negatively affect students' intention to use AI for learning and research.

2.5.7. Personal innovativeness

Personal innovativeness is the degree to which students are willing to experiment with and adopt new technologies (Agarwal & Prasad, 1998). More innovative students tend to be open to AI and eagerly explore new features. Danang reported a positive effect ($\beta = 0.19$) on the intention to use ChatGPT (Nguyen et al., 2024).

H7 (+): Personal innovativeness positively affects students' intention to use AI for learning and research.

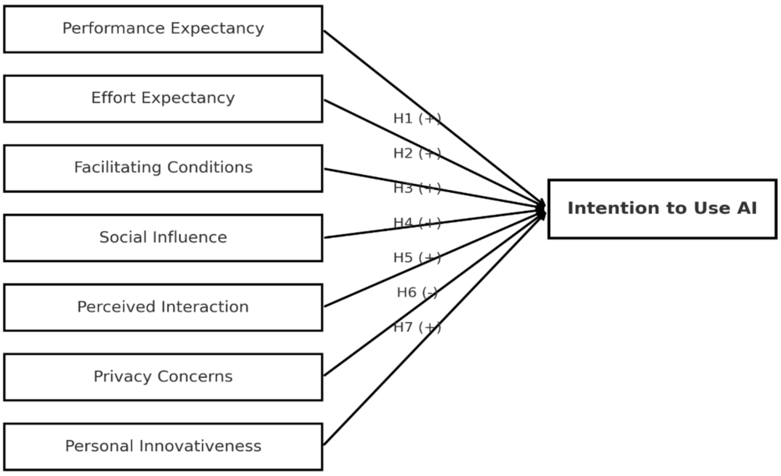

Figure 1 Proposed Research Model.

3. Methodology

3.1. Research Design

This study employs a quantitative approach to test the proposed theoretical model of factors influencing students' intention to use AI in learning and research. The quantitative approach allows the measurement of abstract constructs through observable indicators and the testing of causal relationships between independent and dependent variables via regression analysis. In addition, a descriptive–explanatory design was adopted to clarify the relationships among factors in the extended UTAUT2 model (Venkatesh et al., 2012) within the context of higher education.

3.2. Population and Data Collection

The target population comprised university students in Ho Chi Minh City interested in using AI for learning and research. A convenience sampling method was employed, which is consistent with studies of emerging technologies in academic contexts where time and resources are limited.

Primary data were collected through an online survey designed in Google Forms and distributed via email and student learning groups. Data collection was conducted in August 2025. The questionnaire consisted of two parts: (a) demographic information and (b) measurement items for the study constructs. A total of 300 surveys were distributed, and 258 valid responses were retained for analysis, ensuring reliability and a reasonable degree of representativeness for the target student community.

3.3. Measurement instruments and scales

All the constructs were measured via a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The measurement items were adapted from prior studies, such as Venkatesh et al. (2003, 2012), Camilleri (2024), and Strzelecki (2023) (refer to Table 2).

Table 2 Observed Variables and Scale Sources.

Code	Measurement Item	Source
PE1	I believe AI helps me complete my learning tasks more effectively.	Venkatesh et al. (2003); Camilleri (2024)
PE2	Using AI enhances the quality of my learning.	Venkatesh et al. (2003); Camilleri (2024)
PE3	AI supports me in my academic research.	Venkatesh et al. (2003); Camilleri (2024)
PE4	AI helps me save time when studying.	Venkatesh et al. (2003); Camilleri (2024)
EE1	AI is easy for me to use.	Davis (1989); Venkatesh et al. (2003)
EE2	Learning how to use AI is easy for me.	Davis (1989); Venkatesh et al. (2003)
EE3	I feel comfortable using AI for learning.	Davis (1989); Venkatesh et al. (2003)
EE4	I do not face difficulties when becoming familiar with AI.	Davis (1989); Venkatesh et al. (2003)
FC1	I have the necessary devices (computer, phone, internet) to use AI.	Venkatesh et al. (2003); Strzelecki (2023)
FC2	I receive technical support when needed to use AI.	Venkatesh et al. (2003); Strzelecki (2023)
FC3	I have easy access to AI when needed.	Venkatesh et al. (2003); Strzelecki (2023)
FC4	My university encourages and supports the use of AI.	Venkatesh et al. (2003); Strzelecki (2023)
SI1	My friends think I should use AI in learning.	Venkatesh et al. (2003); Strzelecki (2023)
SI2	My instructors encourage me to use AI.	Venkatesh et al. (2003); Strzelecki (2023)
SI3	Using AI has become common at my university.	Venkatesh et al. (2003); Strzelecki (2023)
PI1	I feel AI responds quickly and appropriately to my needs.	Camilleri (2024)
PI2	I can interact with AI as if I were communicating with a real person.	Camilleri (2024)
PI3	I feel engaged when using AI for learning and research.	Camilleri (2024)
PC1	I am concerned that AI may collect my personal data.	Strzelecki (2023); Nguyen et al. (2024)
PC2	I do not trust how AI stores user information.	Strzelecki (2023); Nguyen et al. (2024)
PC3	I fear that my academic information may be leaked through AI.	Strzelecki (2023); Nguyen Thi Thanh Thuy et al.
PC4	I feel unsafe when sharing learning content through AI.	Strzelecki (2023); Nguyen et al. (2024)
PII1	I am always willing to try new technologies for learning.	Agarwal & Prasad (1998); Strzelecki (2023)
PII2	I am the first in my class to try new learning tools such as AI.	Agarwal & Prasad (1998); Strzelecki (2023)
PII3	I enjoy exploring and learning about new technologies for study.	Agarwal & Prasad (1998); Strzelecki (2023)
BI1	I intend to continue using AI in my learning.	Venkatesh et al. (2003); Camilleri (2024)
BI2	I am willing to recommend AI to others.	Venkatesh et al. (2003); Camilleri (2024)
BI3	I will prioritize AI if I need a learning support tool.	Venkatesh et al. (2003); Camilleri (2024)
BI4	I feel AI is an indispensable part of my learning process.	Venkatesh et al. (2003); Camilleri (2024)

Note: The final questionnaire contained 29 observed items, which were randomly arranged to reduce response bias.

3.4. Data Processing and Analysis

After collection, survey data were cleaned, coded, and entered into SPSS version 26 for processing according to the following steps:

Reliability testing: Cronbach's alpha was used to assess reliability. Items with item–total correlation coefficients less than 0.30 were eliminated. Scales with alpha values ≥ 0.70 were considered acceptable.

Exploratory factor analysis (EFA): Principal axis factoring with varimax rotation was applied. Kaiser–Meyer–Olkin (KMO) values > 0.50 and Bartlett's test of sphericity significance levels < 0.05 were used.

Pearson correlation analysis: Used to test linear associations between independent and dependent variables.

Multiple linear regression analysis: Employed to test hypotheses and determine the influence of each factor on students' intention to use AI. Multicollinearity was checked via the variance inflation factor (VIF) and tolerance values.

ANOVA: ANOVA was used to test the overall fit of the regression model.

All procedures were carried out according to quantitative research standards to ensure the reliability, generalizability, and replicability of the study results.

4. Results

4.1. Descriptive Statistics of the Sample

Following the online survey distribution, 258 valid responses were obtained from university students in Ho Chi Minh City. The sample targeted students who had used or were interested in using AI for learning and research. The demographic characteristics are reported below (Table 3).

Table 3 Demographic characteristics of the respondents.

Criterion	Category	Frequency (n)	Percentage (%)
Gender	Male	62	24.0
	Female	196	76.0
Year of study	Year 1	41	15.9
	Year 2	38	14.7
	Year 3	66	25.6
	Year 4	113	43.8

The sample was predominantly female (76.0%), a distribution that aligns with typical gender ratios in several Ho Chi Minh City universities. With respect to year of study, Year-4 and Year-3 students accounted for the largest shares (43.8% and 25.6%, respectively), suggesting stronger interest and experience with AI among students nearing or engaged in research and internships.

4.2. Reliability analysis (Cronbach's alpha)

Prior to exploratory factor analysis (EFA), internal consistency was assessed via Cronbach's alpha to evaluate the coherence of items within each construct (refer to Table 4). Following Hair et al. (2019), scales with $\alpha \geq .70$ were retained, and items with corrected item–total correlations < .30 were removed.

Table 4 Cronbach's alpha results by construct.

Construct	Items (k)	Cronbach's α	Min. corrected item–total r
Performance Expectancy (PE)	4	.871	.635
Effort Expectancy (EE)	4	.846	.602
Facilitating Conditions (FC)	4	.888	.641
Social Influence (SI)	3	.821	.611
Perceived Interactivity (PI)	3	.864	.673
Privacy Concerns (PC)	4	.789	.502
Personal Innovativeness (PII)	3	.803	.545
Behavioral Intention (BI)	4	.872	.648

Source: SPSS 26 outputs.

All scales showed high reliability (α = .789–.888). With few item–total correlations approaching .50 and most exceeding .60, the indicators demonstrate satisfactory internal homogeneity. All scales were retained for subsequent EFA.

4.3. Exploratory Factor Analysis (EFA)

EFA was conducted to reassess the latent structure of the measurement model and ensure convergent and discriminant properties (Hair et al., 2019). Principal axis factoring with varimax rotation was used. Two prerequisites for EFA were met: KMO ≥ .50 and Bartlett's test $p < .05$.

4.3.1. Exploratory Factor Analysis (EFA)

Twenty-five observed indicators from seven independent constructs were included in the analysis. KMO = .918 indicated "marvelous" sampling adequacy (Kaiser, 1974), and Bartlett's test was significant ($p < .001$), indicating sufficient intercorrelations. Seven factors with eigenvalues > 1 were extracted (Kaiser criterion), explaining 71.834% of the total variance. All factor loadings exceeded .563, surpassing the .50 guideline (Hair et al., 2019). Refer to Table 5 for an EFA summary of the independent variables.

Table 5 EFA summary for independent variables.

Statistic/Setting	Value
KMO	.918
Bartlett's Test Sig.	.000
Extracted factors	7
Extraction criterion	Eigenvalue > 1
Total variance explained	71.834%
Extraction method	Principal Axis Factoring
Rotation	Varimax
Minimum factor loading	.563

Source: SPSS 26 outputs, authors' extraction (2025).

Indicators loaded cleanly on their theorized constructs—PE, EE, FC, SI, PI, PC, and PII—with no problematic cross-loadings, supporting construct convergence and discriminant validity.

4.3.2. EFA results for the dependent variable

Behavioral intention (BI) was measured with four items. KMO = .773 (adequate), and Bartlett's test was significant ($p < .001$). A single factor (eigenvalue = 2.812) accounted for 70.293% of the variance. Loadings exceeded .712, indicating strong unidimensionality and convergence (refer to Table 6).

Table 6 EFA summary for the dependent variables.

Statistic/Setting	Value
KMO	.773
Bartlett's Test Sig.	.000
Extracted factors	1
Eigenvalue	2.812
Variance explained	70.293%
Minimum factor loading	.712

Source: SPSS 26 outputs, authors' extraction (2025).

Collectively, the EFA results confirm acceptable reliability and convergence for both the independent and dependent measures, providing a sound basis for correlation and multiple regression analyses.

4.3.3. Multiple linear regression

After correlation screening, a standard multiple regression (enter method) was estimated to quantify the effects of seven predictors—PE, EE, FC, SI, PI, PII, and PC—on behavioral intention (BI), which is consistent with the extended UTAUT2 framework. All the predictors were entered simultaneously in SPSS 26.

All the predictors exhibited statistically significant effects (sig. < .05). Performance expectancy ($\beta = .291$) was the strongest positive predictor, followed by perceived interactivity ($\beta = .237$) and facilitating conditions ($\beta = .213$). Thus, students are more inclined to use AI when they believe it improves academic effectiveness, when interactions feel smooth and "natural," and when supportive infrastructure and guidance are available. Effort expectancy, social influence, and personal innovativeness also had positive, albeit smaller, effects ($\beta = .127$, .111, and .106, respectively). Privacy concerns had a significant negative effect ($\beta = -.139$), underscoring the deterrent role of data security concerns (refer to Table 7).

Table 7 Regression coefficients predicting Behavioral Intention (BI).

Predictor	B	SE	β	*t*	Sig.	VIF
(Constant)	0.397	0.212	—	1.872	.063	—
PE	0.231	0.046	.291	5.021	.000	1.441
EE	0.108	0.045	.127	2.409	.017	1.325
FC	0.169	0.051	.213	3.294	.001	1.538
SI	0.096	0.042	.111	2.286	.023	1.269
PI	0.198	0.048	.237	4.121	.000	1.492
PII	0.087	0.040	.106	2.152	.032	1.348
PC	−0.112	0.043	−.139	−2.605	.010	1.209

Source: SPSS 26 outputs, survey (2025).

Model fit indices indicated strong explanatory power: $R = .812$, $R^2 = .659$, adjusted $R^2 = .649$, with a standard error of estimate of 0.488 (refer to Table 8). The Durbin–Watson statistic was 1.821 (within the 1–3 acceptability range), suggesting no serious autocorrelation in the residuals.

Table 8 Model summary.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.812	.659	.649	0.488

Source: SPSS 26 outputs, survey (2025).

On the basis of standardized coefficients, the predictive equation for BI is:

$$BI=0.291\,PE+0.127\,EE+0.213\,FC+0.111\,SI+0.237\,PI+0.106\,PII-0.139\,PC \quad (1)$$

ANOVA confirmed the overall model significance, with $F(7, 250) = 58.963$, $p < .001$. (Refer to Table 9).

5. Discussion

The regression results substantiate the extended UTAUT2 framework in the context of higher-education AI. Performance expectancy emerged as the principal driver of intention, emphasizing that perceived academic gains (e.g., improved output quality, time savings) are central to adoption. Perceived interactivity and facilitating conditions are also pivotal, meaning that students value responsive, contextually appropriate AI interactions and dependable access/support.

Effort expectancy, social influence, and personal innovativeness positively contribute to the model, although with smaller effects, indicating that ease of use, normative pressures, and individual openness to novelty still matter. In contrast, privacy concerns significantly deter use, highlighting the need for robust data protection assurances and algorithmic transparency as AI permeates university learning environments.

Table 9 ANOVA results.

Source	SS	df	MS	*F*	Sig.
Regression	98.214	7	14.030	58.963	.000
Residual	50.758	250	0.203		
Total	148.972	257			

Source: SPSS 26 outputs, survey (2025).

Drawing on UTAUT2, the proposed model involves the integration of core acceptance factors with individual-level extensions. Performance expectancy, effort expectancy, facilitating conditions, and social influence demonstrate the cognitive assessment of users regarding AI usefulness, ease of use, available support, and social pressure, which play central roles in technology adoption. On the basis of the extension of UTAUT2, personal innovativeness reflects individual differences in readiness to adopt new technologies, perceived interaction characterizes the experiential and interactive nature of AI systems, and privacy concerns embody perceived risks associated with data and information security. These constructs provide a comprehensive UTAUT2-based research model for better understanding users' intention to adopt AI.

The research findings are similar to those of previous studies, such as Venkatesh et al. (2003) (positive impact of performance expectancy), Camilleri (2024) (positive impact of effort expectancy and perceived interactivity), Strzelecki (2023) (positive impact of social influence), and Nguyen et al. (2024) (positive impact of facilitating conditions and personal innovativeness and negative impact of privacy concerns). Despite the main similarities, this research still has theoretical contributions in terms of recognizing the strongest impact of performance expectancy and the lowest impact of personal innovativeness. This misalignment in terms of the impact level of each factor in comparison with previous studies can be explored further in future related research.

Despite the significant predictability of facilitating conditions for students' intention to use AI, the low average satisfaction score (3.12) reveals a discrepancy between the perceived importance of these factors in students' minds and the reality of institutional support. Facilitating conditions are related to multiple issues, such as access to AI tools, training, technical assistance, and formal integration into teaching and learning processes (Venkatesh et al., 2012). In developing higher-education contexts such as Vietnam, AI adoption is generally driven by students instead of institutionally coordinated, which is also related to inconsistent infrastructure and limited guidance. As emphasized by Zawacki-Richter et al. (2019), the underlined gap can lead to a decrease in users' satisfaction even when facilitating conditions play a critical role. This finding indicates that institutional readiness has not yet fulfilled students' expectations about sustained AI-supported learning systems.

In addition, Perceived Interactivity has a positive effect on intention but only a moderate effect on satisfaction level (3.28), which reflects constraints in existing AI–learner interactions. While generative AI systems can deliver prompt and context-aware responses, they often lack pedagogical depth, adaptive feedback, and reliable conceptual guidance (Kasneci et al., 2023). Students may perceive interactivity as a motivating feature while remaining doubtful and cautious about its instructional quality. These results highlight the need for AI tools built around learning theories and instructional goals and instructor-mediated use to enhance interactive AI learning experiences.

6. Conclusions

Drawing on the quantitative results and multiple regression analysis, several key conclusions can be drawn regarding students' intention to use AI for learning and research in Ho Chi Minh City:

1. Among the seven independent variables entered into the linear regression model, six exert positive effects, and one exerts a negative effect on the intention to use AI. The three strongest positive predictors are performance expectancy (β = 0.291), perceived interactivity (β = 0.237), and facilitating conditions (β = 0.213). In contrast, privacy concerns is the only factor with a significant negative effect (β = −0.139).
2. Combining standardized effects (β) with the lowest mean values (Min) helps identify improvement priorities. Privacy concerns (Min = 2.31) have a clear negative impact and the lowest mean, reflecting widespread student anxiety. The facilitating conditions (Min = 3.12) and perceived interactivity (Min = 3.28) are positive but not yet high, indicating that there is room to improve students' actual experiences.
3. The overall model fit is high (R^2 = 0.659; adjusted R^2 = 0.649), confirming that the extended UTAUT2 factors explain a substantial share of the variance in students' AI usage intention in higher education.

7. Managerial Implications

Grounded in the regression findings and descriptive statistics—and prioritized by (i) standardized effect sizes and (ii) lowest mean scores—the following implications are proposed for universities, instructors, and developers:

Privacy Concerns (PC; β = −0.139; Min = 2.31). As the sole negative predictor with the lowest mean, privacy risk perception is a salient barrier. *Institutional actions:* Issue official guidance on data protection when using AI; integrate digital ethics and privacy modules into skills courses; and clarify what student data are (not) stored when approved tools are used. *Developer actions:* Provide transparent privacy dashboards, granular consent, on-device or privacy-preserving options (e.g., anonymization), and clear model/data retention statements.

Facilitating conditions (FC; β = 0.213; Min = 3.12). The infrastructure and support remain insufficient in practice. *Institutional actions:* Upgrade campus connectivity and device access; expand licenses for AI-enabled academic suites (e.g., writing, analytics); create help desks/peer support labs; and offer short courses for librarians/advisors so that they can provide first-line AI assistance.

Perceived Interactivity (PI; β = 0.237; Min = 3.28). Students perceive a gap between the desired and actual interactive qualities. *Instructor actions:* Run microworkshops on effective prompts (context setting, constraints, and verification routines); embed "AI interaction etiquette" in coursework; and model step-by-step checking and triangulation of AI outputs.

Performance expectancy (PE; β = 0.291; Min = 3.64). The strongest driver can be further reinforced through authentic use cases. *Instructor actions:* Scaffold assignments that require AI for literature summarization, outlining, qualitative coding aids, or exploratory data analysis—paired with reflection memos—to solidify perceived learning gains.

Effort expectancy (EE; β = 0.127; Min = 3.51). Ease of use is acceptable but uneven across students. *Instructor actions:* Normalize light, frequent AI practice in group tasks, in-class activities, and short response writing; maintain "quick-start" guides and template prompts for common academic tasks.

Social Influence (SI; β = 0.111; Min = 3.44). Norms and encouragement can nudge adoption. *Institutional actions:* Run internal campaigns such as "AI Learning Week" or AI-enabled academic challenges; showcase exemplars from faculty and student champions to set positive descriptive norms.

Personal innovativeness (PII; β = 0.106; Min = 3.46). Willingness to experiment exists but is not prominent. *Institutional actions:* Create safe-to-try sandboxes and elective research tasks that leverage AI; invite guest speakers to scholarly AI applications; and recognize student innovations with microcredentials or badges.

8. Declarations

8.1. Ethical considerations

The ethical considerations for the study were as follows: Participant consent – Participants were fully informed about the research objectives, the interview process, and the data usage. Voluntary participation–Participation was completely voluntary. Anonymity and confidentiality – The identities and personal details of the participants were kept confidential, ensuring that no names or identifying information were disclosed.

8.2. Use of artificial intelligence (AI)

The authors declare that the generative artificial intelligence (AI) tool ChatGPT was used exclusively for language editing and/or grammatical improvement. The use of AI did not influence the scientific content, study design, data analysis, data interpretation, results, or conclusions of the manuscript. Full responsibility for the content remains with the authors.

8.3. Conflict of Interest

The authors declare no conflicts of interest.

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