Investigating the Acceptance of Using Artificial Intelligence Platforms in Students' Scientific Research: Survey From Selected Universities in Vietnam

Nguyen Linh Phong, Ho Chi Minh City University of Education, Vietnam
Ngo Gia Bao, Ho Chi Minh City University of Education, Vietnam

The Paris Conference on Education 2026
Official Conference Proceedings

Abstract

The rapid advancement of artificial intelligence platforms has significantly influenced and transformed the ways in which students use and access these technologies in contemporary scientific research. This study aims to explore the acceptance of artificial intelligence platforms in scientific research among university students in Vietnam. Data were collected from 350 students and analyzed using the CB-SEM model. The survey results indicate that AI platforms have a strong impact on students' attitudes and perceptions regarding their use when conducting research or studying courses related to scientific research at universities in Vietnam. In addition, this study initially provides a reliable theoretical foundation that may support universities in implementing AI in scientific research in an effective and well-regulated manner. This may contribute to increasing acceptance of use and enabling the effective utilization of the potential of artificial intelligence in related academic activities.

Keywords: acceptance of use, artificial intelligence platforms, CB-SEM, university students, scientific research

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Introduction

In recent years, artificial intelligence (AI) has developed extremely rapidly, moving from simple data processing systems to intelligent platforms capable of supporting learners in thinking, analysis and knowledge exploration. This development has profoundly changed how people access information and use technology in everyday life, especially in higher education, where learners increasingly depend on digital tools for learning and scientific research (Wang & Lu, 2025). Recent studies show that students are the group with the highest level of access to and use of AI because of their technological adaptability and the growing need to process academic information today (Wolfe et al., 2025).

In the context of globalization and digital transformation in education, the use of AI (AI) platforms as tools to support learning and scientific research has become a common trend in many countries, especially in Vietnam (Tran et al., 2025). Many studies indicate that AI helps students improve the effectiveness of literature searching, data analysis and research idea formation, thereby contributing to the improvement of academic quality (Nasni Naseri & Abdullah, 2024). However, the level of students' acceptance and use of AI is not uniform and depends considerably on individual perceptions of benefits, ease of use and the suitability of the technology for learning and research goals (Nagy & Hajdú, 2021).

In Vietnam, the development and application of AI in higher education are being strongly promoted within the framework of national digital transformation and educational innovation. Some universities have initially encouraged students to use AI tools in learning and scientific research, especially in fields that require information processing and large scale data handling (Chung et al., 2024). Domestic studies show that Vietnamese students have relatively positive attitudes toward using AI, although concerns remain regarding the reliability, transparency and controllability of AI generated outputs (Le & Bui, 2025). This indicates the need for systematic research on students' acceptance of AI use in the current context of Vietnamese higher education (Doan, 2025; Phan et al., 2024).

To explain learners' technology acceptance and use behavior, the Technology Acceptance Model (TAM) proposed by Davis has become one of the foundational theoretical frameworks and is widely used in educational research (Davis, 1989). According to this model, learners' intention to use technology is mainly influenced by two factors, namely perceived usefulness and perceived ease of use. Subsequent studies have confirmed the effectiveness of TAM in predicting acceptance behavior toward new technologies, including AI platforms in higher education (Nasni Naseri & Abdullah, 2024).

Although TAM is a solid foundational theoretical framework, studies indicate that in the current context of rapidly expanding AI technologies with highly personalized features, a more comprehensive theoretical framework is needed to capture psychological, social and infrastructural aspects fully (Acosta Enriquez et al., 2024). In this regard, the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) emerges as an optimal tool because it not only inherits the strengths of TAM but also allows researchers to expand and add context specific factors (Wang & Lu, 2025). Based on this theoretical foundation, this study was designed and developed using the UTAUT2 model to analyze undergraduate students' acceptance of using AI platforms in scientific research in Vietnam.

The study aims to clarify the current state of students' acceptance of AI use in scientific research and to identify the influencing factors and correlations among these factors in the present context of Vietnamese higher education. More specifically, the authors focus on answering the following two main research questions:

1. How is the acceptance of using AI platforms in scientific research among Vietnamese undergraduate students currently manifested?
2. Which factors influence AI acceptance, and how are these factors correlated?

Literature Review

Studies on AI Acceptance in Vietnam

In Vietnam, direct studies on the acceptance of Artificial Intelligence (AI) use in scientific research remain relatively scarce. Most current works focus on the application of AI in higher education, especially the use of AI chatbots in learning and academic writing. For example, recent surveys show that undergraduate students tend to evaluate positively the knowledge support role of ChatGPT in the learning process (Thai, 2023). In addition, studies on academic ethics also indicate that using AI in research entails risks related to source verification and scientific integrity (Tran et al., 2025).

Moreover, national policy documents such as the National Strategy on Research, Development and Application of AI through 2030 have created an institutional foundation for expanding AI application in scientific research and higher education (Prime Minister, 2021). However, studies that directly measure the intention and level of AI acceptance among lecturers, researchers and research groups in Vietnam have not yet been widely published, reflecting a significant academic gap in this field.

Studies on AI Acceptance in International Contexts

Internationally, the acceptance of AI use in academic activities and scientific research has been studied relatively comprehensively. Many studies rely on classical theoretical models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT or UTAUT2) to explain technology acceptance behavior in academic environments (Venkatesh et al., 2003).

A conceptual analysis based on the UTAUT2 model shows that factors such as performance expectancy, facilitating conditions and habit have a significant influence on AI acceptance in university contexts (Acosta Enriquez et al., 2024). In addition, a large scale international survey of medical researchers indicates that although AI chatbots are highly valued for their ability to support information searching, writing and research synthesis, many scientists remain cautious because of concerns about accuracy, transparency and scientific responsibility (Ng et al., 2025).

Recent studies on generative AI also emphasize the importance of balancing technological benefits with ethical issues in research, especially in ensuring the integrity and authenticity of academic results (Dwivedi et al., 2023).

The literature overview shows that the acceptance of AI use in scientific research is receiving increasing attention internationally. However, in Vietnam, the authors find that most studies have approached AI mainly through educational or policy contexts rather than focusing on researchers' intention and behavior in accepting AI use. Therefore, studying this topic in the Vietnamese context is necessary to supplement the academic gap and provide a theoretical basis for developing policies for effective, responsible and more appropriate AI use in line with current standards of students' scientific research.

Theoretical Basis

Concept and Role of Artificial Intelligence (AI)

In the digital era, Artificial Intelligence (AI) is no longer viewed merely as a technical support tool but has become a factor that reshapes students' approaches to information and research, especially through the popularity of AI platforms such as ChatGPT and Claude. According to the definition of Dwivedi et al. (2021), AI is a computational system capable of simulating human cognitive abilities in processing data, learning from experience, recognizing patterns and making decisions based on large datasets (Dwivedi et al., 2021). From this perspective, the authors observe that AI platforms appear as an indispensable part of the research ecosystem, where deep learning algorithms and large language models (LLMs) are gradually changing how humans access, interpret and generate knowledge every day. In educational contexts, AI should be regarded as an active learning and research tool that changes how students accept the use of these platforms in scientific research within the current university environment.

Furthermore, Burger et al. emphasize that AI can function as a "digital research assistant" that supports scientists in identifying research gaps, synthesizing knowledge and processing complex unstructured datasets. This study indicates that the combination of AI's superior productivity and humans' independent critical capacity is a key condition for creating sustainable academic value (Burger et al., 2023). Similarly, Larios Soldevilla et al. (2025) demonstrate that integrating AI tools into the research process helps university learners improve productivity, literature synthesis and academic coherence while also promoting critical thinking capacity in the digital environment.

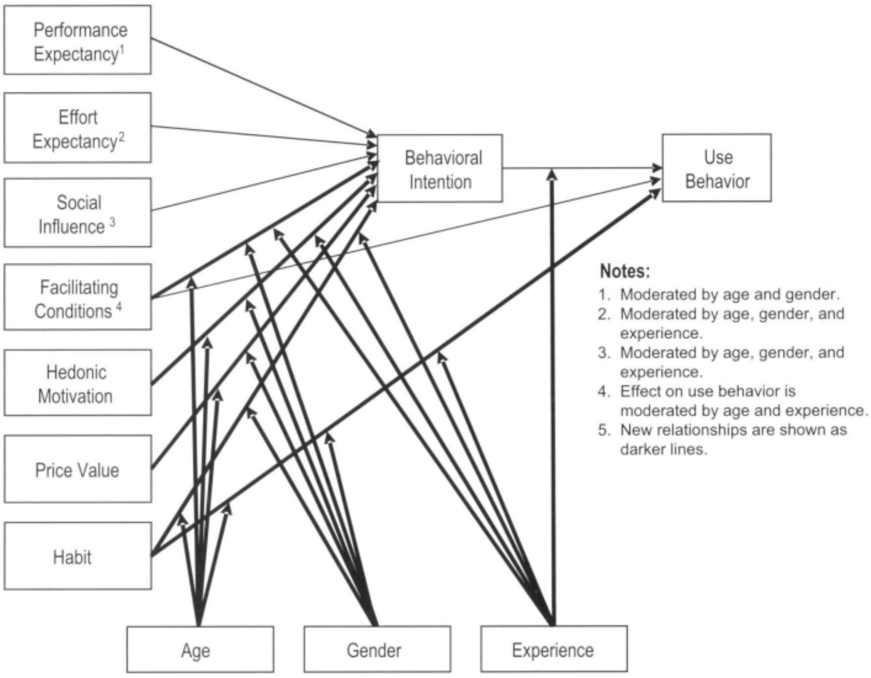
Based on the above points, AI also plays a role in optimizing processes from idea formation to the generation of results. More specifically, AI tools can automate literature review, data extraction and complex quantitative analysis, helping save time and reduce bias (Wang & Lu, 2025). In addition, Larios Soldevilla et al. state that AI helps reduce language and editorial barriers, thereby allowing researchers to focus more on creative activities and critical thinking, which are two core elements of modern scientific knowledge (Larios Soldevilla et al., 2025).

Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)

To explain the psychosocial factors that influence AI acceptance behavior among researchers, especially university students, the authors argue that the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) developed by Venkatesh et al. is the most suitable theoretical framework for this topic, particularly in the current academic research context of students.

This model was developed from the original UTAUT by adding factors that reflect individual user behavior, allowing the description of voluntary behaviors and personalized experiences (Venkatesh et al., 2003). The authors believe that this is particularly suitable for the current scientific research context, where AI use is both a necessary professional need and an individual choice. Interactive components in the UTAUT2 model:

Figure 1
Research Model: UTAUT2



According to Venkatesh et al. (2012), technology acceptance is influenced by seven main factors. First, performance expectancy reflects the belief that using AI will enhance research productivity, quality and accuracy. Next, effort expectancy reflects perceived ease in operating the technology. In the AI context, this relates to the ability to learn prompt engineering skills and verify outputs (Venkatesh et al., 2012).

From a broader perspective, social influence is understood as normative pressure from the academic community and publication policies, for example, current requirements on disclosing AI use in international journals (Ganjavi et al., 2024). At the same time, facilitating conditions, including technological infrastructure, technical support and usage guidance, determine the ability to transform intention into actual use behavior.

Unlike traditional technology acceptance models, UTAUT2 adds factors that reflect intrinsic motivation such as hedonic motivation and habit, which are particularly important in academic environments where the exploration and experimentation of new tools can generate creative inspiration (Venkatesh et al., 2012).

Finally, price value reflects the balance between cost, such as subscription fees for premium AI tools, and the academic benefits generated by AI platforms, such as research productivity and output quality.

Model of Acceptance and Use of AI Platforms in Scientific Research

When the authors synthesize the theoretical perspectives and previous research findings, it can be seen that AI, especially current AI platforms based on large language models, is gradually becoming an inseparable component of scientific research activities among university students.

AI not only plays the role of a simple technical support tool but also participates directly in the process of idea formation, knowledge synthesis, data analysis and the completion of academic products. According to the authors, accepting and using AI in research is therefore no longer a random phenomenon but the result of complex interactions among personal, social and technological factors.

In that context, the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) is considered an appropriate theoretical framework for explaining students' acceptance behavior toward AI platforms in scientific research. By integrating instrumental factors such as performance expectancy, effort expectancy and facilitating conditions, social factors such as social influence, and intrinsic motivational factors such as hedonic motivation, habit and price value, UTAUT2 allows a more comprehensive approach to AI use behavior in academic environments, where technology use is both voluntary and strongly influenced by scientific norms and future professional requirements.

From this theoretical basis, the authors argue that developing a model of acceptance of AI platform use in scientific research based on UTAUT2 is not only academically meaningful but also accurately reflects the research practices of undergraduate students in the digital era. This model not only provides a foundation for identifying factors that influence intention and behavior in AI use but also creates a premise for the empirical analyses in the following sections and contributes to proposing appropriate management and policy implications for orienting effective, responsible and sustainable AI use in higher education.

Research Methodology

In this study, the authors used a quantitative research method. The quantitative research was designed to test the model using CB SEM. In the initial stage of the study, the authors reviewed and systematized works related to AI acceptance and technology acceptance behavior in academic and research contexts, thereby forming the theoretical framework, developing hypotheses and identifying appropriate measurement scales. The authors then collected survey data from university students to evaluate the measurement model and the structural model.

Data Collection Tools

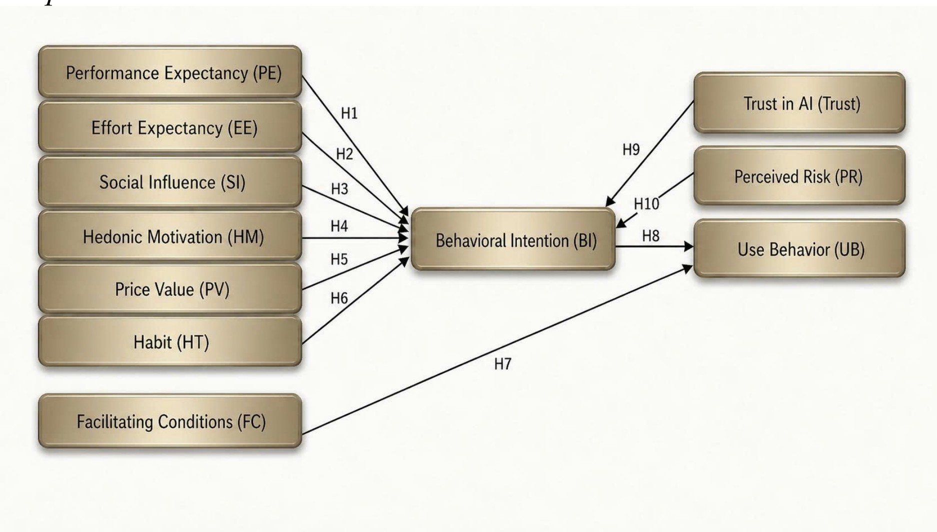
In this study, the authors used Zotero to collect, store and manage all documents for the literature review. The sources were mainly searched from academic databases and tools such as Google Scholar, ScienceDirect and other appropriate reputable academic platforms.

In implementation, quantitative data were collected from students through a structured questionnaire to measure acceptance level and intention to use AI platforms in scientific research activities. After collection, the data were processed using SPSS for coding, value processing, checking and descriptive statistics. Next, this study used Jamovi to run the CB SEM model. CFA was conducted to confirm the measurement scales of concepts related to AI acceptance, followed by structural model testing to assess model fit and test hypotheses about factors influencing acceptance of AI platform use in scientific research.

Research Model Framework, Proposed Hypotheses and Measurement Scale

Based on the synthesis of the theoretical foundations above, the proposed research model establishes causal relationships between the seven independent factors of UTAUT2 (PE, EE, SI, FC, HM, PV, HT) and two dependent variables, namely Behavioral Intention and Use Behavior. In this model, Behavioral Intention plays a core mediating role, reflecting the psychological readiness of researchers before incorporating AI into the scientific process. At the same time, the model can be extended with additional context specific variables such as Trust and Perceived Risk, following the suggestion of Lai et al. (2024), in order to reflect the particular context of academic research, where integrity, responsibility and transparency are all placed at the forefront.

Figure 2
Proposed Research Model



Based on the UTAUT2 model and previous studies, this study proposes the following hypotheses:

(1) Factors influencing Behavioral Intention (BI): H1: Performance Expectancy (PE) has a positive effect on students' intention to use AI platforms in scientific research; H2: Effort Expectancy (EE) has a positive effect on students' intention to use AI platforms in scientific research; H3: Social Influence (SI) has a positive effect on students' intention to use AI platforms in scientific research; H4: Hedonic Motivation (HM) has a positive effect on students' intention to use AI platforms in scientific research; H5: Price Value (PV) has a positive effect on students' intention to use AI platforms in scientific research; H6: Habit (HT) has a positive effect on students' intention to use AI platforms in scientific research.

(2) Factors influencing Use Behavior (UB): H7: Facilitating Conditions (FC) have a positive effect on students' use behavior regarding AI platforms in scientific research; H8: Behavioral Intention (BI) has a positive effect on students' use behavior regarding AI platforms in scientific research.

(3) Factors extended according to the academic research context: H9: Trust has a positive effect on students' intention to use AI platforms in scientific research; H10: Perceived Risk has a negative effect on students' intention to use AI platforms in scientific research.

The following measurement scale was adapted to the context of students' scientific research to ensure content validity. The citation sources combine the original UTAUT2 model (Venkatesh et al., 2012) and recent academic AI studies (Dwivedi et al., 2021, 2023; Lai et al., 2024; Wang & Lu, 2025). All observed variables were measured using a five-point Likert scale (1 = Strongly disagree; 5 = Strongly agree).

Research Results

Descriptive Statistics of the Research Sample

Research data were collected from a sample of 350 undergraduate students in Vietnam. The data cleaning process showed that no observations were missing (missing = 0), ensuring the integrity of the analytical dataset.

Regarding demographic structure, the survey sample was relatively evenly distributed across gender groups, with males accounting for 54.0% and females accounting for 46.0%. In terms of year of study, most participating students were first year students (52.9%) and second year students (40.0%), while students in the third year and above accounted for a smaller proportion (7.1%). Notably, the frequency of using AI (AI) platforms in students' academic environment was very high. Up to 81.4% of students selected the highest level of use (level 5), and 10.9% reported frequent use (level 4). The detailed structure of the research sample is presented in Table 1.

Table 1
Demographic Characteristics of the Research Sample

Characteristic	Classification	Frequency (N = 350)	Percentage (%)
Gender	Male	189	54.0%
	Female	161	46.0%
Field of study	Natural Sciences	107	30.6%
	Social Sciences	104	29.7%
	Educational Sciences	120	34.3%
	Foreign Languages	19	5.4%
Year of study	Year 1	185	52.9%
	Year 2	140	40.0%
	Year 3 and above	25	7.1%
AI use frequency	Never	5	1.4%
	Rarely	6	1.7%
	Occasionally	16	4.6%
	Frequently	38	10.9%
	Very frequently	285	81.4%

Assessment of Scale Reliability and Exploratory Factor Analysis (EFA)

Before structural analysis, the reliability of the scales was tested using Cronbach's alpha. The results show that all latent constructs achieved high internal consistency. Specifically, the Cronbach's alpha coefficients of the variables far exceeded the acceptable threshold, ranging from 0.742 (Use Behavior, UB) to 0.893 (Performance Expectancy, PE, and Facilitating Conditions, FC). The item rest correlations of all observed variables were greater than 0.30, confirming that no observed variable was removed from the measurement model.

Table 2
Results of Scale Reliability Testing (Cronbach's Alpha)

Symbol	Conceptual construct	Number of observed variables	Cronbach's alpha
PE	Performance Expectancy	4	0.893
EE	Effort Expectancy	3	0.886
SI	Social Influence	3	0.864
HM	Hedonic Motivation	3	0.874
PV	Price Value	3	0.878
HT	Habit	3	0.883
FC	Facilitating Conditions	3	0.893
TR	Trust	3	0.881
PR	Perceived Risk	3	0.891
BI	Behavioral Intention	3	0.761
UB	Use Behavior	3	0.742

Next, exploratory factor analysis (EFA) was conducted using principal axis factoring and Promax rotation. The KMO (Kaiser Meyer Olkin) index reached 0.780 (greater than 0.5), and Bartlett's Test of Sphericity produced statistically significant results (X2 = 6490, df = 561, $p < .001$), confirming that the data were fully suitable for factor analysis. The extraction process produced 10 factors with cumulative variance extracted reaching 67.57%, exceeding the 50% standard.

In terms of factor structure, most observed variables loaded strongly on their corresponding theoretical factors, with factor loadings greater than 0.50. Notably, the variables belonging to Behavioral Intention (BI) and Use Behavior (UB) tended to load together on the sixth factor. This convergence often appears in technology acceptance studies at a high practical application stage, reflecting a very close relationship between intention and behavior. This structural issue was further examined through confirmatory factor analysis (CFA).

Confirmatory Factor Analysis (CFA)

The measurement model was evaluated using confirmatory factor analysis (CFA) to rigorously confirm unidimensionality, convergent validity and discriminant validity. The overall model testing results show an exceptionally ideal fit with the actual data: Chi square = 460, degrees of freedom df = 472, p value = 0.643. Since $p > 0.05$, the difference between the theoretical and actual covariance matrices was not statistically significant.

Other model fit indices also reached optimal levels compared with current academic standards: CFI = 1.00, TLI = 1.00, SRMR = 0.0310 and RMSEA = 0.000. The standardized factor loadings of all observed variables, presented in Table 3, were high, ranging from 0.672 to 0.897, and all were statistically significant at $p < .001$, with Z values ranging from 12.9 to 20.1. These results provide strong empirical evidence of convergent validity and confirm that the measurement model is fully suitable for conducting structural equation modeling (SEM).

Table 3
Standardized Factor Loadings From CFA

Latent variable	Observed variable	Standardized estimate	Z value	P value
Performance Expectancy (PE)	PE1	0.806	17.5	< .001
	PE2	0.841	18.7	< .001
	PE3	0.823	18.1	< .001
	PE4	0.822	18.1	< .001
Effort Expectancy (EE)	EE1	0.855	18.9	< .001
	EE2	0.860	19.1	< .001
	EE3	0.834	18.3	< .001
Social Influence (SI)	SI1	0.812	17.2	< .001
	SI2	0.843	18.1	< .001
	SI3	0.817	17.4	< .001
Hedonic Motivation (HM)	HM1	0.805	17.3	< .001
	HM2	0.848	18.5	< .001
	HM3	0.855	18.8	< .001
Price Value (PV)	PV1	0.897	20.1	< .001
	PV2	0.817	17.7	< .001
	PV3	0.809	17.5	< .001
Habit (HT)	HT1	0.866	19.2	< .001
	HT2	0.809	17.5	< .001
	HT3	0.863	19.1	< .001
Facilitating Conditions (FC)	FC1	0.880	20.0	< .001
	FC2	0.835	18.5	< .001
	FC3	0.859	19.3	< .001
Trust (TR)	TR1	0.885	19.9	< .001
	TR2	0.839	18.4	< .001
	TR3	0.809	17.5	< .001
Perceived Risk (PR)	PR1	0.852	19.0	< .001
	PR2	0.856	19.1	< .001
	PR3	0.858	19.1	< .001
Behavioral Intention (BI)	BI1	0.672	13.2	< .001
	BI2	0.769	15.7	< .001
	BI3	0.715	14.3	< .001
Use Behavior (UB)	UB1	0.721	13.9	< .001
	UB2	0.677	12.9	< .001
	UB3	0.698	13.4	< .001

Structural Model Testing (SEM)

The structural equation model (SEM) was used to test the research hypotheses (H1 to H10). The fit of the proposed theoretical model with the empirical data was evaluated as excellent. Specifically, X2 = 470, df = 479, p = 0.605; other indices were CFI = 1.000, TLI = 1.002, RMSEA = 0.000 and SRMR = 0.033. The SEM effect analysis table provides evidence for conclusions regarding the hypotheses:

Figure 3
SEM Path Model

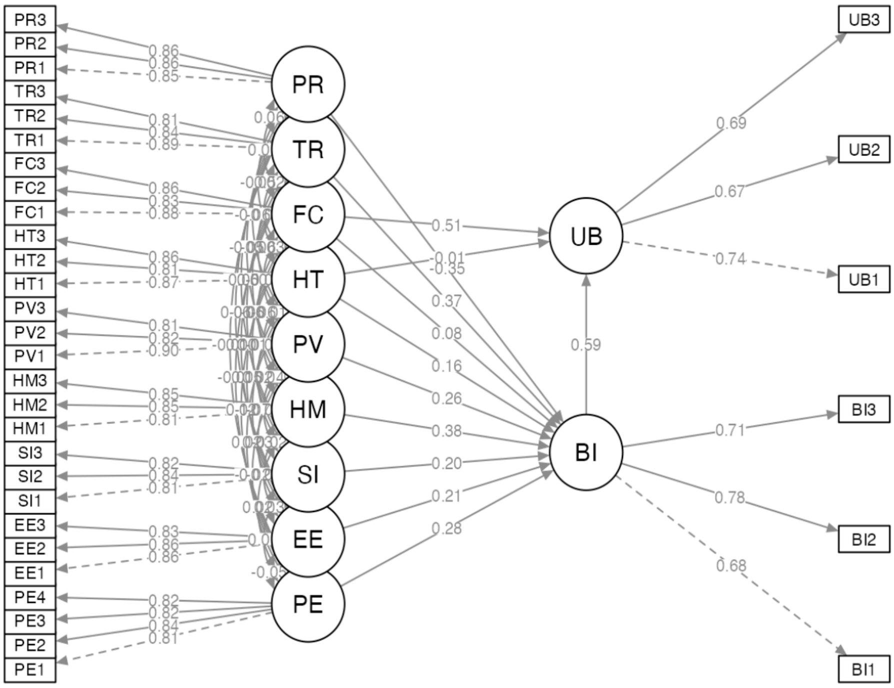


Table 4
Results of Research Hypothesis Testing (SEM Model)

Hypothesis	Structural relationship	Standardized coefficient (β)	Z value	P value	Conclusion
H1	Performance Expectancy (PE) to Behavioral Intention (BI)	0.279	5.470	< .001	Accepted
H2	Effort Expectancy (EE) to Behavioral Intention (BI)	0.211	4.278	< .001	Accepted
H3	Social Influence (SI) to Behavioral Intention (BI)	0.204	4.097	< .001	Accepted
H4	Hedonic Motivation (HM) to Behavioral Intention (BI)	0.378	6.987	< .001	Accepted
H5	Price Value (PV) to Behavioral Intention (BI)	0.257	5.160	< .001	Accepted
H6	Habit (HT) to Behavioral Intention (BI)	0.163	3.313	< .001	Accepted
H7	Facilitating Conditions (FC) to Use Behavior (UB)	0.510	8.768	< .001	Accepted
H8	Behavioral Intention (BI) to Use Behavior (UB)	0.588	8.447	< .001	Accepted
H9	Trust to Behavioral Intention (BI)	0.368	6.955	< .001	Accepted
H10	Perceived Risk (PR) to Behavioral Intention (BI)	−0.350	−6.684	< .001	Accepted

For Behavioral Intention (BI): The data show that all proposed independent factors had significant effects on the intention to use AI in scientific research. Among them, Hedonic Motivation (HM) ($\beta = 0.378$) and Trust (TR) ($\beta = 0.368$) were the two factors with the strongest positive influence. The expanded factor in the academic context, Perceived Risk (PR), served as the main barrier, with a strong and statistically significant negative effect ($\beta = -0.350$, $p < .001$) on intention to use.

For Use Behavior (UB): Actual application behavior regarding AI platforms was directly and strongly promoted by Behavioral Intention (BI) ($\beta = 0.588$, $p < .001$) and the support of Facilitating Conditions (FC) ($\beta = 0.510$, $p < .001$). Infrastructural conditions and academic support play a core role in transforming psychological intention into actual AI use behavior in students' research processes. Note that the study also recorded that FC had no statistically significant direct effect on BI, with $\beta = 0.093$, which is consistent with the original UTAUT2 theory.

Discussion

Discussion of Key Findings

This study successfully applied the extended UTAUT2 model to explain acceptance and use behavior regarding AI (AI) platforms in scientific research among undergraduate students in Vietnam. The results of structural equation modeling (SEM) confirmed the systematic nature and fit of the proposed model, while also producing several important findings specific to the academic context.

First, the central role of Hedonic Motivation (HM) and Trust. Unlike traditional educational technologies, where Performance Expectancy often occupies an absolutely dominant position, the data from this study show that Hedonic Motivation ($\beta = 0.378$) and Trust ($\beta = 0.368$) are the two factors with the strongest effects on intention to use AI. This reflects the fact that large language models, such as ChatGPT and Claude, are not merely dry computational tools but also provide intuitive interactive experiences, making the process of knowledge exploration and idea seeking less monotonous. More importantly, in the scientific research environment, trust in the quality of technological outputs is a prerequisite. When students trust that AI provides reliable information and does not reduce academic integrity, their intention to apply it increases significantly, which is fully consistent with the findings of Ng et al. (2025).

Second, the dual effect of technological perception and ethical barriers. Performance Expectancy (PE), Effort Expectancy (EE) and Price Value (PV) all have positive and significant effects on intention to use. Clearly, students perceive AI as a productivity lever that helps optimize effort from literature review to data analysis. However, the study also indicates that Perceived Risk (PR) is a significant barrier ($\beta = -0.350$). Concerns about information accuracy, namely AI hallucinations, as well as risks related to publication ethics and dependence that may erode independent critical thinking capacity, are well founded. This finding fills a theoretical gap in Vietnam regarding psychological barriers when applying AI in scientific research and confirms the view of Tran et al. (2025) regarding source verification risks.

Third, the transformation from intention into behavior. The results show that Use Behavior (UB) is directly influenced not only by Behavioral Intention (BI) ($\beta = 0.588$) but also by Facilitating Conditions (FC) ($\beta = 0.510$). Regardless of how strong students' intention is, actual use behavior in scientific research can occur effectively only when supported by technological infrastructure and especially by legal corridors and transparent guidance from universities. This highlights the role of higher education institutions in shaping an AI use environment.

Management and Policy Implications

From the empirical results, the study proposes several important implications for higher education institutions and educational managers in Vietnam to promote the use of AI in scientific research effectively and responsibly:

(1) Developing an institutional framework and transparent guidance handbook: To minimize Perceived Risk (PR) and strengthen students' Trust, universities should urgently issue clear regulations on AI ethics in academia. This regulatory framework should define the boundary between using AI as a tool to support thinking and AI generated fraud or plagiarism. Making the citation process and reporting of the extent of AI use in articles and theses transparent will help students feel more secure when using this technology.

(2) Integrating AI literacy into training programs: Because Performance Expectancy and Effort Expectancy positively affect intention to use, universities should organize workshops and intensive training courses on prompt engineering and independent data verification skills. Helping students master technology not only increases ease of use but also eliminates passive dependence on machines.

(3) Upgrading facilitating conditions: The strong relationship between Facilitating Conditions and Use Behavior suggests that universities should consider providing legal access to licensed AI platforms, such as ChatGPT Plus and Copilot Pro, for students and researchers. This helps address the barrier related to Price Value (PV), ensures equality in technology access and thereby improves the overall quality of scientific research at educational institutions.

Research Limitations and Future Directions

Although this study contributes important theoretical and practical foundations, it still has certain limitations. First, the study used convenience sampling focused on undergraduate students; therefore, its representativeness may not fully cover the entire academic ecosystem. Second, the research data were cross sectional data, reflecting users' perceptions at a specific point in time, while AI technology is evolving at a very rapid pace.

In the future, subsequent studies could expand the survey scope to lecturers, postgraduate researchers and experts to obtain a multidimensional comparative perspective. In addition, longitudinal research models combined with qualitative analysis through in depth interviews would help decode more precisely the adaptation process and changes in the cognitive structure of researchers in response to the increasingly deep intervention of AI in knowledge production processes.

Conclusion

This study was conducted to explore and comprehensively evaluate the factors influencing the acceptance of using AI (AI) platforms in scientific research activities among students at universities in Vietnam. Based on the UTAUT2 model extended with two academic context variables, Trust and Perceived Risk, quantitative data collected from 350 students were successfully tested using covariance based structural equation modeling, CB SEM.

The empirical results confirmed the excellent fit of the proposed theoretical model with the empirical data. The study confirms that Hedonic Motivation and Trust are core factors with the strongest positive effects on students' intention to apply AI. In addition, foundational factors including Performance Expectancy, Effort Expectancy, Price Value, Habit and Social Influence all play important roles in shaping technology acceptance attitudes. In particular, the study clarified the negative effect of Perceived Risk, reflecting learners' legitimate concerns about data accuracy and issues related to academic integrity. Finally, the work demonstrates that actual AI use behavior in the research process is strongly promoted by the transformation of individual intention, together with the system of facilitating conditions regarding infrastructure and policy support from universities.

In summary, the development and presence of AI platforms are gradually reshaping how students access information, process data and create knowledge. This work not only initially fills the theoretical gap regarding AI acceptance behavior among researchers in Vietnam but also provides a reliable practical basis. Based on these findings, higher education institutions can formulate appropriate strategies, legal frameworks and training programs to maximize the potential of AI while effectively controlling risks to ensure ethical standards in academic activities.

Acknowledgements

The authors would like to express sincere gratitude to the students who participated in this study and generously shared their experiences and perspectives of AI acceptance in scientific research. We also extend our appreciation to Ho Chi Minh City University of Education, and university students that supported the data collection process.

References

Acosta Enriquez, B. G., Ramos Farroñan, E. V., Villena Zapata, L. I., Mogollon Garcia, F. S., Rabanal León, H. C., Angaspilco, J. E. M., & Bocanegra, J. C. S. (2024). Acceptance of AI in university contexts: A conceptual analysis based on UTAUT2 theory. *Heliyon*, *10*(19), e38315. https://doi.org/10.1016/j.heliyon.2024.e38315

Burger, B., Kanbach, D. K., Kraus, S., Breier, M., & Corvello, V. (2023). On the use of AI based tools like ChatGPT to support management research. *European Journal of Innovation Management*, *26*(7), 233–241. https://doi.org/10.1108/EJIM-02-2023-0156

Chung, D. T., Thanh, N. C. M., Thu, N. V. A., Trinh, H. D., & Trinh, V. T. T. (2024). Factors affecting the behavior of using AI tools in learning among students at universities in Ho Chi Minh City. *Journal of Finance and Marketing research*, 112–125. https://doi.org/10.52932/jfm.v15i6.544

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

Doan, T. C. (2025). Using ChatGPT to support students' learning: A study at Tan Trao University. *Vietnam Journal of Education*, *25*(15), 53–58. https://tcgd.tapchigiaoduc.edu.vn/index.php/tapchi/article/view/3711

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., ... Williams, M. D. (2021). AI (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., Wright, R. (2023). Opinion paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Ganjavi, C., Eppler, M. B., Pekcan, A., Biedermann, B., Abreu, A., Collins, G. S., Gill, I. S., & Cacciamani, G. E. (2024). Publishers' and journals' instructions to authors on use of generative AI in academic and scientific publishing: Bibliometric analysis. *BMJ*, *384*, e077192. https://doi.org/10.1136/bmj-2023-077192

Lai, C. Y., Cheung, K. Y., Chan, C. S., & Law, K. K. (2024). Integrating the adapted UTAUT model with moral obligation, trust and perceived risk to predict ChatGPT adoption for assessment support: A survey with students. *Computers and Education: AI*, *6*, 100246. https://doi.org/10.1016/j.caeai.2024.100246

Larios Soldevilla, O. A., Mendoza Ibarra, V., Urdanegui Sibina, R., Zilberman, J., Lizola Margolis, P. E., Flores Peraltilla, A. V., Herz Ghersi, J., Valencia Brenis, M., & Aviles Valdez, J. R. (2025). Adoption of AI tools and their impact on the academic research output of business school students. *Cogent Education*, *12*(1), 2556892. https://doi.org/10.1080/2331186X.2025.2556892

Le, T. T. T., & Bui, N. T. A. (2025). Acceptance of AI applications in personal finance. *Journal of Finance and Marketing research*, *16*(1), 56–69. https://doi.org/10.52932/jfm.v16i1.467

Nagy, S., & Hajdú, N. (2021). Consumer acceptance of the use of AI in online shopping: Evidence from Hungary. *Amfiteatru Economic*, *23*(56), 155–173. https://doi.org/10.24818/EA/2021/56/155

Nasni Naseri, R. N., & Abdullah, M. S. (2024). Understanding AI technology adoption in educational settings: A review of theoretical frameworks and their applications. *Information Management and Business Review*, *16*(3(I)), 174–181. https://doi.org/10.22610/imbr.v16i3(I).3963

Ng, J. Y., Maduranayagam, S. G., Suthakar, N., Li, A., Lokker, C., Iorio, A., Haynes, R. B., & Moher, D. (2025). Attitudes and perceptions of medical researchers towards the use of AI chatbots in the scientific process: An international cross sectional survey. *The Lancet Digital Health*, *7*(1), e94–e102. https://doi.org/10.1016/S2589-7500(24)00202-4

Phan, T. K., Nguyen, D. C., & Dinh, T. D. (2024). Application of AI in teaching and scientific research at universities. *Vietnam Journal of Education*, *24*(24), 14–19. https://tcgd.tapchigiaoduc.edu.vn/index.php/tapchi/article/view/2677

Prime Minister. (2021). Decision No. 127/QD TTg promulgating the National Strategy on Research, Development and Application of AI through 2030. https://vanban.chinhphu.vn/default.aspx?pageid=27160&docid=202565

Thai, T. C. T. (2023). Attitudes and expectations of English language teacher education students toward ChatGPT: A study at Hanoi National University of Education. *Vietnam Journal of Education*, *23*(10), 51–56. https://tcgd.tapchigiaoduc.edu.vn/index.php/tapchi/article/view/767

Tran, T. H., Le, T. N. T., Le, T. T. V., & Le, H. N. (2025). AI assisted references: Verification issues and ensuring integrity in scientific research in Vietnam. *Journal of Science Hanoi Open University*, 70. https://doi.org/10.59266/houjs.2025.665

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

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178. https://doi.org/10.2307/41410412

Wang, W., & Lu, Y. (2025). Survey on Chinese users' acceptance of AI assistants: Expanding technology acceptance model. *Scientific Reports*, 15, 33535. https://doi.org/10.1038/s41598-025-18123-6

Wolfe, D., Price, M., Choe, A., Kidd, F., & Wagner, H. (2025). Revisiting UTAUT for the age of AI: Understanding employees' AI adoption and usage patterns through an extended UTAUT framework. *arXiv*. https://arxiv.org/abs/2510.15142

Contact emails: phongnl@hcmue.edu.vn
baongo20015@gmail.com