

Research Article

Cite this article: Nguyen, T. H., & Ha, D. A. T. (2025). Exploring Vietnamese Students' Intention to Adopt AI-Powered Study Tools: Integrating TPB and TAM. *Educational Process: International Journal*, 16, e2025283. <https://doi.org/10.22521/edupij.2025.16.283>

Received April 27, 2025

Accepted June 6, 2025

Published Online June 27, 2025

Keywords: Artificial Intelligence, AI-Powered Study Tools, TAM, TPB, Gen Z Students

Author for correspondence:

Thanh Huong Nguyen

✉ huong.nguyenthanh4@hust.edu.vn

✉ Hanoi University of Science and Technology, Vietnam

**OPEN ACCESS**

© The Author(s), 2025. This is an Open Access article, distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>), which permits unrestricted re-use, distribution, and reproduction, provided the original article is properly cited.

Exploring Vietnamese Students' Intention to Adopt AI-Powered Study Tools: Integrating TPB and TAM

Thanh Huong Nguyen , Do Anh Tu Ha

Abstract

Background/purpose. The study addresses the lack of clear policies and ethical concerns surrounding AI use in Vietnamese universities, where debates continue over balancing AI's benefits with risks of academic misconduct. This study seeks to investigate determinants of students' use of AI-powered study tools, by applying the Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM), to inform better teaching strategies and AI tool development.

Materials/methods. Using PLS-SEM analysis, we examine the roles of perceived behavioral control (PBC), perceived usefulness (PU), perceived ease of use (PEOU), computer self-efficacy (CS), attitudes toward using AI (ATU), perceived enjoyment (PE), and subjective norms (SN) in shaping students' adoption intentions. The study also investigates the mediating role of behavioral intention (BI) in the adoption process.

Results. The analysis of 313 valid responses collected online via Google Forms indicates that PBC, CS, and ATU positively influence BI, suggesting that Gen Z students are more likely to adopt AI tools when they feel confident using them and perceive them as beneficial. PU and PEOU positively impact ATU, reinforcing the adoption process, while PE and SN do not significantly affect BI.

Conclusion. Findings suggest that Vietnamese Gen Z students prioritize functional benefits, such as academic performance and efficiency, over entertainment value. These insights emphasize the need for AI tools that align with students' learning needs, offering valuable implications for educators and developers in Vietnam's evolving educational landscape.

1. Introduction

Industry 4.0, characterized by the integration of artificial intelligence (AI), the Internet of Things (IoT), big data, and cyber-physical systems, has introduced cutting-edge solutions to improve efficiency, optimize processes, and revolutionize traditional workflows (Pivoto et al., 2021). Among these technologies, AI has become a game-changer not only in sectors such as manufacturing, healthcare, and finance but also increasingly in education. The educational landscape is undergoing a significant shift as AI-powered tools reshape teaching and learning experiences, promising personalized learning, increased engagement, and improved outcomes (Steinbauer et al., 2021; Yang, 2019).

Within educational research, frameworks like the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) are frequently employed to examine how new technologies are adopted. These models identify key factors such as perceived usefulness, attitudes, and behavioral control that influence technology acceptance among learners and educators (Maheshwari, 2021; Scherer et al., 2019). However, despite the growing interest, few studies have combined TAM and TPB to comprehensively explore how students in higher education adopt AI-based learning tools, especially within emerging markets such as Vietnam.

Vietnam's educational system is at a crossroads regarding AI integration. While AI presents opportunities to enhance learning and research, many universities have yet to establish clear policies on its appropriate use in academic settings (A. Nguyen et al., 2023; Uoc, 2023). Furthermore, concerns about the overreliance on AI tools, which are sometimes perceived as a form of academic misconduct, highlight the ethical dilemmas surrounding AI in education (Chao et al., 2021; H. M. Nguyen & Goto, 2024). These challenges underscore the need for deeper insight into students' intentions and real-world usage of AI technologies within their academic environments.

Although AI-powered educational tools are increasingly available, prior research has not sufficiently addressed the complex interaction between social influence, individual competencies, and hedonic motivations affecting AI adoption among Vietnamese students (Nguyen et al., 2023; Van Le et al., 2021). This study aims to fill this gap by integrating TAM and TPB frameworks to examine the technological and behavioral determinants of AI adoption in higher education. Focusing on university and college students in Hanoi, where AI adoption is emerging, this research seeks to (1) identify key factors influencing AI adoption based on TPB and TAM, (2) explore behavioral intention as a mediator between perceived behavioral control, perceived enjoyment, computer self-efficacy, attitudes toward AI use, and actual AI adoption, and (3) offer recommendations to guide effective teaching and learning strategies. The findings contribute both theoretical insights and practical implications for educators and AI developers, supporting the ethical and effective integration of AI in higher education. Therefore, this research aims to answer the following questions: Which key factors affect students' intentions to use AI-driven tools? How do psychological and behavioral factors shape actual AI use? What implications can support ethical and effective AI adoption in educational settings?

2. Literature Review

2.1. Theory of Planned Behavior (TPB)

The TPB, building on the Theory of Reasoned Action (TRA), is widely used to predict BI (Ustadi & Mat, 2023). Unlike the TRA, the TPB incorporates PBC, which accounts for factors that may enable or constrain an individual's ability to carry out a behavior. This model identifies three key predictors of intention: behavioral attitudes, subjective norms (SN), and PBC. These factors influence intentions, which, in turn, predict actual behavior when individuals have control over the action (Hsu & Huang, 2010; Kiriakidis, 2015; Shalender & Sharma, 2021).

Given its broad application in education, the TPB has been used to examine both learner and teacher behaviors, shedding light on how attitudes, social pressures, and confidence shape various educational actions (Maheshwari, 2021; Urton et al., 2023). This research applies the TPB to explore the intentions of university students in Vietnam regarding the adoption of AI-based learning tools.

2.2. Technology Acceptance Model (TAM)

The TAM, developed by Fred D. Davis (Davis, 1989) and later expanded by Bagozzi (Bagozzi et al., 1992), serves as a fundamental theory for explaining the factors that influence individuals' adoption of new technologies (Martín-García et al., 2022; Mugo et al., 2017). It builds on the TRA but emphasizes two specific factors: perceived usefulness (PU) and perceived ease of use (PEOU). These factors play a vital role in influencing users' attitudes toward technology and their intentions to use it. TAM has been widely applied and validated in diverse fields, including banking (Ahmad, 2018), consumer behavior (Jokar et al., 2017; Tam et al., 2018), tourism (Alkhatib & Bayouq, 2021; X. Chen & Li, 2020), and healthcare (Chong & Chan, 2012; Kang & Hwang, 2022). These studies confirm the model's robustness and consistency in examining how technology is adopted.

Within the educational field, TAM has been extensively applied to explore the adoption of digital tools by both students and teachers to improve teaching and learning processes (Al-Adwan et al., 2023; Eraslan Yalcin & Kutlu, 2019; Weng et al., 2018). The research adapts TAM to examine how Vietnamese students adopt AI-based study tools, emphasizing how PU and PEOU affect their attitudes and intentions to use these tools. While TAM is a relatively straightforward model, it can be expanded or modified in various ways. Consequently, numerous studies have integrated TAM with other theories, enriching the literature on technology adoption (Bryan & Zuva, 2021; Gangwar et al., 2015; Ha & Nguyen, 2019).

2.3. Hypotheses and Proposed Model

Building on the above analysis, the integration of TPB and TAM constructs in this study provides a comprehensive framework to examine students' AI adoption, addressing both social and technological factors influencing their intentions. While TAM focuses on PU and PEOU (Bagozzi et al., 1992), TPB incorporates the influence of SN, ATU, and PBC (Ajzen, 1991). When integrated, TPB complements TAM by addressing its limitations, particularly in accounting for social and behavioral dimensions (Hameed & Counsell, 2014; Troise et al., 2021; Wang et al., 2022). This combined approach is especially effective for exploring complex behaviors like students' adoption of AI-powered study tools, providing valuable insights for advancing both research and practice in educational technology. Accordingly, this study investigates the following hypotheses:

The Effect of Perceived Behavioral Control (PBC) on Behavioral Intention

PBC reflects an individual's evaluation of how easy or challenging it would be to carry out a particular behavior, as well as their perceived ability to achieve the desired outcomes associated with that behavior. Factors such as personal limitations or external barriers can influence both the actual capability to act and the perception of control over it (Kiriakidis, 2015; Troise et al., 2021). The TPB suggests that this construct is particularly relevant in scenarios where individuals may face limitations that restrict their ability to act freely (Ajzen, 1991).

In the educational context, PBC reflects students' beliefs in their ability to effectively utilize AI-based learning tools for learning and overcome challenges they may face, such as limited technical expertise or restricted access to necessary technology. When students perceive they have sufficient control over using these tools, whether through training, resources, or support, they are more inclined to form intentions to embrace them (Kucuk et al., 2020; Wang et al., 2022). According to the TPB, higher perceived control is directly associated with stronger behavioral intentions. Based on these insights, the following hypothesis is proposed:

H1: *PBC has a positive impact on students' intentions to utilize AI-powered tools.*

The Effect of Subjective Norms (SN) on Behavioral Intention

SN refers to a person's understanding of whether important people, such as parents, peers, or instructors, believe they should engage in a specific behavior. This influence depends on normative beliefs and their willingness to align with others' expectations (Ham et al., 2015; Ustadi & Mat, 2023).

In educational settings, SN significantly shapes students' behavioral intentions, particularly when peers or instructors express positive attitudes toward technology. Students tend to be more inclined to use tools that are seen as important or endorsed by those in their social environment, especially in collaborative or classroom contexts (Hussein, 2018; Wang et al., 2022). In this study, subjective norms reflect the degree to which students feel social pressure from important individuals to use AI-powered tools. Based on this understanding, the following hypothesis is proposed:

H2: *Subjective norms have a positive impact on students' intentions to utilize AI-powered tools.*

The Effect of Perceived Enjoyment (PE) on Behavioral Intention

Intrinsic motivation forms the basis of the concept of PE, as defined by Hussein (Hussein, 2018). It aligns with the idea of hedonic motivation introduced by Kim and Hall (2019), referring to the degree of fun and pleasure experienced while using a specific technology (Y.-W. Chang et al., 2023). Kim and Hall further elaborate that PE describes the enjoyment derived from using a system for the sake of the activities themselves, rather than for any functional or performance-based results (Kim & Hall, 2019). Their research, along with others, underscores the important role that PE plays in shaping individuals' intentions to interact with technological tools.

In educational settings, perceived enjoyment (PE) connects students' sense of fun with the perceived effectiveness of their digital learning experiences (Su & Chiu, 2021). Research has shown that enjoyment positively influences students' attitudes toward learning platforms, increasing their likelihood of adopting these systems (Hussein, 2018; Khalid, 2014; Roslan et al., 2021). This is consistent with the idea that engaging and enjoyable interactions with technology can motivate students to incorporate it into their learning processes. Therefore, we propose the following hypothesis:

H3: *Perceived enjoyment has a positive impact on students' intentions to utilize AI-powered tools.*

The Effect of Computer Self-Efficacy (CS) on Behavioral Intention

Self-efficacy describes a person's confidence in their capability to organize and carry out tasks effectively (Bandura, 1986). CS, in general, has been found to impact how individuals behave and their likelihood to engage with technology, as people with higher self-efficacy tend to view technology as accessible and manageable (Simsek, 2011).

In educational contexts, CS reflects students' confidence or self-belief in their ability to understand, operate, and effectively utilize technological tools. Those with stronger self-efficacy are more inclined to view AI-powered tools as manageable and beneficial, resulting in a greater likelihood of adoption. Conversely, students who have low self-confidence in their abilities may doubt their capabilities, resulting in negative attitudes toward using such tools (Nurhikmah et al., 2021; Saadé & Kira, 2009). Studies have shown that self-efficacy significantly influences attitudes and intentions toward adopting technologies like Learning Management Systems and e-learning platforms (Arpaci, 2017; Hayashi et al., 2004). Accordingly, students who possess high self-efficacy are more inclined to confidently embrace AI-powered tools. In light of this, the following hypothesis is suggested:

H4: *Computer self-efficacy has a positive impact on students' intentions to utilize AI-powered tools.*

Attitudes Toward Using AI-powered tools (ATU) and Its Impact on Behavioral Intention

Attitudes are shaped by the beliefs necessary to engage in a behavior (Ajzen, 1991). They are defined as an individual's positive or negative feelings associated with performing a specific behavior. An individual will hold a favorable attitude toward a behavior if they believe that performing it will lead to mostly positive outcomes (Ha & Nguyen, 2019; Shah Alam & Mohamed Sayuti, 2011; Ustadi & Mat, 2023). Past studies have identified a significant direct relationship between attitudes and intentions toward a behavior, particularly in contexts such as green product usage (Teng et al., 2015; Zaremohzzabieh et al., 2021), internet banking (Bashir & Madhavaiah, 2015; Y.-C. Chang et al., 2020), and electronic commerce (Fauzi et al., 2021; Hernández García et al., 2011). Based on this, we propose the following hypothesis:

H5: *Students' attitudes have a positive impact on their intentions to use AI-powered tools.*

Perceived Usefulness (PU) and Its Impact on Attitude

PU is widely acknowledged as a key determinant influencing users' attitudes and intentions to adopt technology. It reflects the belief that a particular system or tool can improve one's performance (Davis, 1989; Davis, 1993). Users tend to engage with systems and technologies they consider advantageous for their productivity, task efficiency, and overall job performance (Elkaseh et al., 2015; Kucukusta et al., 2015; Saparudin et al., 2020). Conversely, if users believe a system may negatively affect their performance, they are less inclined to use it (Yuen et al., 2021). The dimensions of PU, including its ability to simplify tasks, boost productivity, and improve job effectiveness, have shown significant influence across various domains, such as banking (Prayudi et al., 2022; Tan & Teo, 2000), healthcare (Jokar et al., 2017; Kang & Hwang, 2022), tourism (Bimaruci et al., 2020; Teng et al., 2024), and consumption (Ha & Nguyen, 2019; Tam et al., 2018; Troise et al., 2021). In educational contexts, PU directly impacts learners' attitudes toward and satisfaction with technology-based tools (Al-Adwan et al., 2023; Buabeng-Andoh, 2018; Keržič et al., 2019; Scherer et al., 2019). In light of this, the following hypothesis is formulated:

H6: *Perceived usefulness has a positive impact on students' attitudes toward using AI-powered tools.*

Perceived Ease of Use (PEOU) and Its Impact on Attitude

PEOU refers to the extent to which individuals believe that utilizing a specific system will require minimal effort (Saparudin et al., 2020). Within the TAM, PEOU plays a crucial role in shaping users' attitudes and intentions toward adopting technology. When users view a system as user-friendly and straightforward, they have a greater tendency to develop positive attitudes, which enhance their intention and may even encourage them to integrate it into their daily routines (Naeem et al., 2023). In this study, PEOU represents students' belief that AI-powered tools for learning are straightforward and user-friendly. Such tools simplify exploration and usage, increasing satisfaction and fostering positive attitudes. Therefore, the following hypothesis is formulated:

H7: *Perceived ease of use has a positive impact on students' attitudes toward using AI-powered tools.*

The Effect of Behavioral Intention and Actual Behavior in Using AI Tools

Both the TPB and the TAM propose that an individual's actions are driven by their intention to perform a behavior, which is influenced by their personal attitude toward it and the social norms or pressures they perceive around them. Intention is viewed as the most reliable indicator of behavior, as it reflects a person's readiness to act and is considered the direct precursor to the behavior itself (Ajzen, 1991). Several recent studies have repeatedly highlighted a significant link between intention

and behavior, especially in the context of education (Maheshwari, 2021; Wang et al., 2022). In light of this, the following hypothesis is suggested:

H8: *Students' intentions have a positive impact on their actual behavior of using AI-powered tools.*

Drawing from the review of prior studies and the theoretical foundations, we propose a research model as shown in Figure 1.

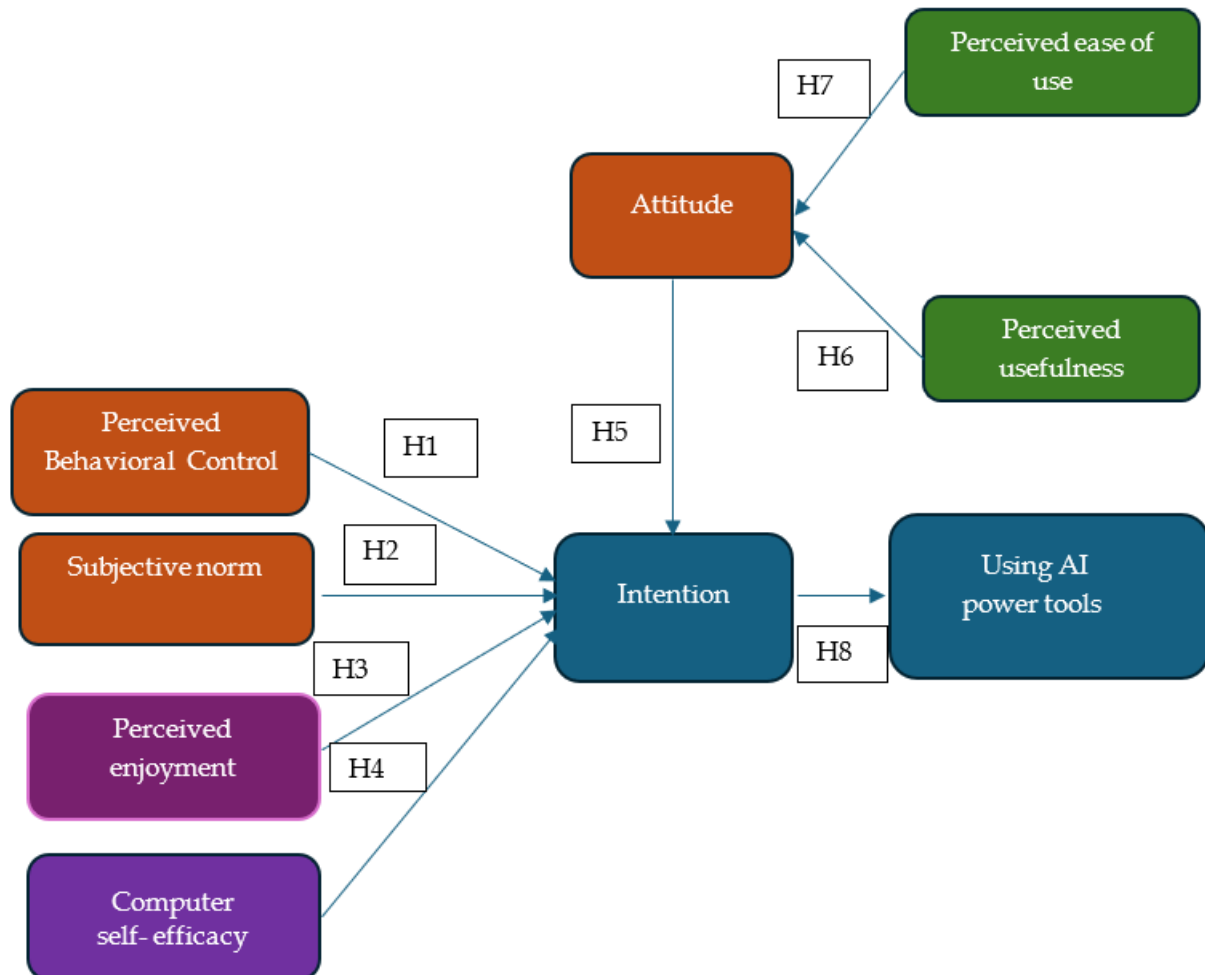


Figure 1. The Proposed Research Model

3. Methodology

3.1. Sample and Data Collection

A quantitative correlational design was adopted to examine relationships between behavioral and technological variables influencing students' intention to adopt AI tools. Convenience sampling was used due to accessibility to university students, consistent with prior studies (Van Le et al., 2021).

The minimum required sample size (175) was determined via G*Power analysis ($f^2 = 0.15$, power = 0.95, $\alpha = 0.05$, 5 predictors). Additionally, following Bollen's rule for convenience sampling (Bollen, 1989), 225 responses were suggested based on 35 observed variables. The final dataset included 313 valid responses, exceeding both thresholds.

Data collection was conducted through an online survey using Google Forms between October and December 2024, distributed through Facebook, Zalo, and Microsoft Teams. Inclusion criteria included current university/college enrollment in Hanoi and prior use or awareness of AI-powered learning tools. Those unaware of such tools were excluded. Each participant completed only one

submission and was informed of the study's purpose and their right to withdraw. The collected data was analyzed using Microsoft Excel 2024 and SmartPLS 4.0.9.8, with the main demographic information presented in Table 1.

Table 1. Demographic Characteristics of Participants

Characteristics	Number (n)	Percentage (%)
Total	313	100
Gender		
Male	252	80.5
Female	57	18.2
Other	4	1.3
Study Year		
Year 1	83	26.5
Year 2	122	39.0
Year 3	82	26.2
Year 4	19	6.1
Year 5	5	1.6
Other	2	0.6
Study Program		
Standard	288	92.0
High quality	18	5.8
Part-time	2	0.6
Other	5	1.6
Major		
Economics	9	2.9
Foreign languages	2	0.6
Engineering	277	88.5
Education	1	0.3
Arts	2	0.6
Other	22	7.0

3.2. Research Measurement

A structured questionnaire was used as the main instrument for gathering data. All constructs included in the model were based on prior research. The exact wording of the items can be found in Table A1 in the Appendix.

Specifically, PU variable was assessed with 4 items referenced from Davis (1989) and Fathema et al. (2015) (Davis, 1989; Fathema et al., 2015). These items were designed to assess students' perceived usefulness of using AI tools in learning so that an example item states, "I find that using AI-powered tools significantly improves my academic performance."

PEOU was measured by 4 items referenced from Davis (1989) and Salloum (2019) (Davis, 1989; Salloum et al., 2019), to assess students' perceived ease of use of AI in studying. One PEOU example item is "I find AI-powered tools clear and easy to understand."

PBC was measured by 5 items, derived from Taylor & Todd (1995) (Taylor & Todd, 1995), to assess students' perceived behavioral control for using AI tools. One example item of PBC states, "I believe I can successfully utilize any AI-powered tools."

PE was measured by 3 items, referenced by Salloum et al. (2019) (Salloum et al., 2019), to assess students' enjoyment while using AI tools in learning, with one example stating, "I find using AI-powered tools interesting".

ATU was measured by 5 items, referenced by Fathema et al. (2015) (Fathema et al., 2015), to assess students' attitudes toward using AI, with one example being "I have a positive view of using AI tools."

SN was evaluated by 5 items, adapted from Salloum et al. (2019) (Salloum et al., 2019), to assess the social influences affecting students' use of AI tools in learning. A sample item says, "Most people who are important to me think that I should use AI-powered tools."

CS was measured by 3 items, referenced from Fathema et al. (2015) (Fathema et al., 2015), to assess students' computer self-efficacy, with one example "I am confident in my self-learning ability when using AI-powered tools."

BI was assessed by 3 items, referenced by Fathema et al. (2015) and Salloum et al. (2019) (Fathema et al., 2015; Salloum et al., 2019), to capture students' intentions to utilize AI tools in their learning process. One example of BI items states, "I intend to use AI-powered tools in the long term."

AB was measured by 3 items, referenced by Göncz & Tian (2020) (Göncz & Tian, 2020), to illustrate students' actual behavior in adopting AI tools in learning, with one example "I have experience using AI-powered tools in my studies and work."

As a result, a total of 35 survey questions were designed and implemented for this study. Participants rated each item using a five-point Likert scale, with responses ranging from "strongly disagree" (1) to "strongly agree" (5). To maintain the accuracy of meaning, the items were translated from English into Vietnamese and then back-translated to verify consistency with the original content. The questionnaire's validity was ensured through expert back-translation. A pilot test confirmed clarity.

3.3. Data Analysis

We used a structural equation modeling (SEM) approach, specifically the partial least squares method (PLS-SEM), to test the proposed hypotheses. Compared to covariance-based structural equation modeling (CB-SEM), PLS-SEM presents specific benefits, including its independence from assumptions related to data normality and large sample sizes (Hair et al., 2019). PLS-SEM is a widely used method in social sciences, recognized as an appropriate technique for multivariate analysis (Hair

et al., 2019; Peng & Lai, 2012). This approach is suitable for use with both small and large datasets and does not depend on the assumption of normally distributed data (Hair et al., 2019; Ringle et al., 2020). The process involves two main stages: first, assessing the outer measurement model, followed by evaluating the inner structural model (Henseler et al., 2009). Given that the survey data likely did not conform to the normal distribution assumption, PLS-SEM was considered the most suitable method.

The measurement model was employed to evaluate the quality of the observed indicators, as well as the reliability, convergent validity, and discriminant validity of the measurement scales. The reliability of a single observed variable refers to how much variance in the observed indicator can be explained by the underlying latent construct, which is assessed through the standardized outer loadings (Götz et al., 2009). According to Hair et al., 2019, observed indicators with outer loadings of 0.7 or higher are generally considered highly acceptable, whereas those with loadings below 0.7 are recommended for removal (Chin, 1998).

Reliability was evaluated using both Cronbach's Alpha and Composite Reliability (CR), with values above 0.7 considered acceptable benchmarks (Hair et al., 2019; Henseler & Sarstedt, 2013). Convergent validity was determined based on the requirement that factor loadings exceed 0.5 (Ringle et al., 2020). Discriminant validity was evaluated by contrasting the square roots of the average variance extracted (AVE) with the correlation coefficients within the model, as well as examining the Heterotrait-Monotrait ratio of correlations (HTMT) values. Based on Fornell and Larcker (1981), discriminant validity is established when the square root of the AVE values is greater than the corresponding correlation coefficients (Fornell & Larcker, 1981). Additionally, HTMT values should be below 0.9 to confirm discriminant validity (Henseler et al., 2015).

The structural model relationships were measured using PLS-SEM with a bootstrapping approach (5,000 resamples) to determine the significance of the correlations (Henseler et al., 2009). The assessment process involved testing for multicollinearity (using VIF), evaluating the coefficient of determination (R^2), and conducting hypothesis testing (Hair Jr et al., 2021).

4. Results

4.1. Measurement Model

First, the outer loadings of the observed variables were assessed. An observed variable with an outer loading below 0.7 may not meaningfully represent its associated factor and should be considered for removal. After removing indicators with outer loadings below 0.7, the remaining indicators all exhibited outer loadings above 0.7, confirming their significance in the model (Table 2).

Table 2. Outer Loadings (Second Iteration)

	AB	ATU	BI	CS	PBC	PE	PEOU	PU	SN
AB1	0.876								
AB2	0.905								
AB3	0.829								
ATU1		0.841							
ATU2		0.855							
ATU3		0.885							
ATU4		0.864							

	AB	ATU	BI	CS	PBC	PE	PEOU	PU	SN
ATU5		0.861							
BI1			0.914						
BI2			0.922						
BI3			0.897						
CS1				0.856					
CS2				0.886					
CS3				0.806					
PBC1					0.857				
PBC2					0.827				
PBC3					0.868				
PE1						0.872			
PE2						0.855			
PE3						0.883			
PEOU1							0.871		
PEOU2							0.871		
PEOU4							0.819		
PU1								0.839	
PU2								0.825	
PU3								0.878	
PU4								0.885	
SN1									0.714
SN2									0.784
SN3									0.787
SN4									0.707
SN5									0.739

Table 3 shows that Cronbach's alpha values range from 0.804 to 0.913, and CR values range from 0.812 to 0.936, indicating good reliability as they exceed the 0.7 threshold. The AVE values range from 0.558 to 0.830, exceeding the suggested minimum of 0.5, thereby confirming convergent validity.

Table 3. Construct Reliability, Convergent Validity (Second Iteration)

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AB	0.842	0.868	0.904	0.758
ATU	0.913	0.915	0.935	0.741
BI	0.898	0.899	0.936	0.830
CS	0.808	0.814	0.886	0.723
PBC	0.811	0.819	0.887	0.724
PE	0.842	0.859	0.904	0.757
PEOU	0.814	0.814	0.890	0.729
PU	0.880	0.883	0.917	0.735
SN	0.804	0.812	0.863	0.558

Furthermore, the discriminant validity of the constructs was examined based on the Fornell-Larcker criterion and the assessment of the HTMT correlations. Table 4 indicates that the square root of AVE for the SN variable is 0.747, which is lower than its correlations with ATU, BI, and CS. Therefore, the discriminant validity of SN is violated.

Table 4. Fornell- Lacker Criterion (Second Iteration)

	AB	ATU	BI	CS	PBC	PE	PEOU	PU	SN
AB	0.871								
ATU	0.693	0.861							
BI	0.737	0.773	0.911						
CS	0.670	0.757	0.711	0.850					
PBC	0.606	0.725	0.687	0.682	0.851				
PE	0.556	0.757	0.618	0.672	0.688	0.870			
PEOU	0.542	0.693	0.641	0.632	0.732	0.690	0.854		
PU	0.632	0.717	0.714	0.643	0.706	0.662	0.687	0.857	
SN	0.688	0.788	0.759	0.766	0.647	0.647	0.622	0.651	0.747

The study went further to assess the HTMT in light of the limitations of the AVE technique. Table 5 shows that the HTMT criterion for SN with ATU and CS significantly exceeds the 0.9 threshold, violating discriminant validity. Removing highly correlated SN indicators and samples did not improve the results, leading to SN's elimination in the third model iteration.

Table 5. HTMT (Second Iteration)

	AB	ATU	BI	CS	PBC	PE	PEOU	PU	SN
AB									
ATU	0.776								
BI	0.827	0.849							
CS	0.805	0.876	0.832						
PBC	0.723	0.833	0.798	0.837					
PE	0.645	0.854	0.699	0.805	0.818				
PEOU	0.640	0.801	0.748	0.778	0.895	0.823			
PU	0.725	0.795	0.800	0.756	0.825	0.755	0.810		
SN	0.832	0.914	0.876	0.950	0.792	0.781	0.758	0.764	

Table 6 demonstrates that all observed variables have outer loadings above 0.7, validating their significance within the model.

Table 6. Outer Loadings (Third Iteration)

	AB	ATU	BI	CS	PBC	PE	PEOU	PU
AB1	0.876							
AB2	0.905							
AB3	0.829							
ATU1		0.841						
ATU2		0.855						
ATU3		0.885						
ATU4		0.864						
ATU5		0.861						
BI1			0.914					
BI2			0.922					
BI3			0.897					
CS1				0.856				
CS2				0.886				
CS3				0.806				
PBC1					0.857			

	AB	ATU	BI	CS	PBC	PE	PEOU	PU
PBC2					0.827			
PBC3					0.868			
PE1						0.872		
PE2						0.855		
PE3						0.883		
PEOU1							0.871	
PEOU2							0.871	
PEOU4							0.819	
PU1								0.839
PU2								0.825
PU3								0.878
PU4								0.885

The results in Table 7 reveals that both Cronbach's Alpha and Composite Reliability (CR) for all measurement scales are above 0.7, indicating strong reliability. Moreover, the Average Variance Extracted (AVE) values exceed 0.5 across all scales, supporting convergent validity.

Table 7. Construct Reliability, Convergent Validity (Third Iteration)

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AB	0.842	0.868	0.904	0.758
ATU	0.913	0.915	0.935	0.741
BI	0.898	0.899	0.936	0.830
CS	0.808	0.814	0.886	0.723
PBC	0.811	0.819	0.887	0.724
PE	0.842	0.859	0.904	0.757
PEOU	0.814	0.814	0.890	0.729
PU	0.880	0.883	0.917	0.735

Table 8 shows that the square root of the AVE surpasses the correlations among the latent variables, confirming discriminant validity. Additionally, Table 9 further supports this validity, as all HTMT values are below 0.9.

Table 8. Fornell- Lacker Criterion (Third Iteration)

	AB	ATU	BI	CS	PBC	PE	PEOU	PU
AB	0.871							
ATU	0.693	0.861						
BI	0.737	0.773	0.911					
CS	0.670	0.757	0.711	0.850				
PBC	0.606	0.725	0.687	0.682	0.851			
PE	0.556	0.757	0.618	0.672	0.688	0.870		
PEOU	0.542	0.693	0.641	0.632	0.732	0.690	0.854	
PU	0.632	0.717	0.714	0.643	0.706	0.662	0.687	0.857

Table 9. HTMT (Third Iteration)

	AB	ATU	BI	CS	PBC	PE	PEOU	PU
AB								
ATU	0.776							
BI	0.827	0.849						
CS	0.805	0.876	0.832					
PBC	0.723	0.833	0.798	0.837				
PE	0.645	0.854	0.699	0.805	0.818			
PEOU	0.640	0.801	0.748	0.778	0.895	0.823		
PU	0.725	0.795	0.800	0.756	0.825	0.755	0.810	

4.2. Structural Model and Hypothesis Test

Path analysis was conducted using structural equation modeling with the PLS-SEM estimation method to examine the primary research hypotheses. To enhance the stability of the results, a bootstrapping procedure was implemented with 5,000 subsamples. The estimation results are presented in Table 10. Except for the PE → BI relationship, which is not significant as its p-value exceeds 0.05, all other relationships are significant with p-values below 0.05. This non-significant result may suggest that perceived enjoyment has a less important impact on behavioral intention in this academic context, where factors like usefulness or ease of use may have a stronger influence. Consequently, hypothesis H2 is rejected, while hypotheses H1, H3, H4, H5, H6, and H7 are supported.

Table 10. Path Coefficient Results and T-Value Analysis (Hypothesis Testing)

Hypothesis	Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	p-value	Hypothesis support or reject
H1	PBC -> BI	0.214	0.214	0.064	3.359	0.001	Supported
H3	PE -> BI	-0.048	-0.047	0.065	0.743	0.457	Rejected
H4	CS -> BI	0.237	0.235	0.074	3.200	0.001	Supported
H5	ATU -> BI	0.475	0.476	0.072	6.606	0.000	Supported
H6	PU -> ATU	0.456	0.457	0.064	7.084	0.000	Supported
H7	PEOU -> ATU	0.379	0.380	0.054	7.022	0.000	Supported
H8	BI -> AB	0.737	0.737	0.028	25.954	0.000	Supported

Figure 2 presents the structural model, displaying the path coefficients and corresponding p-values for each construct.

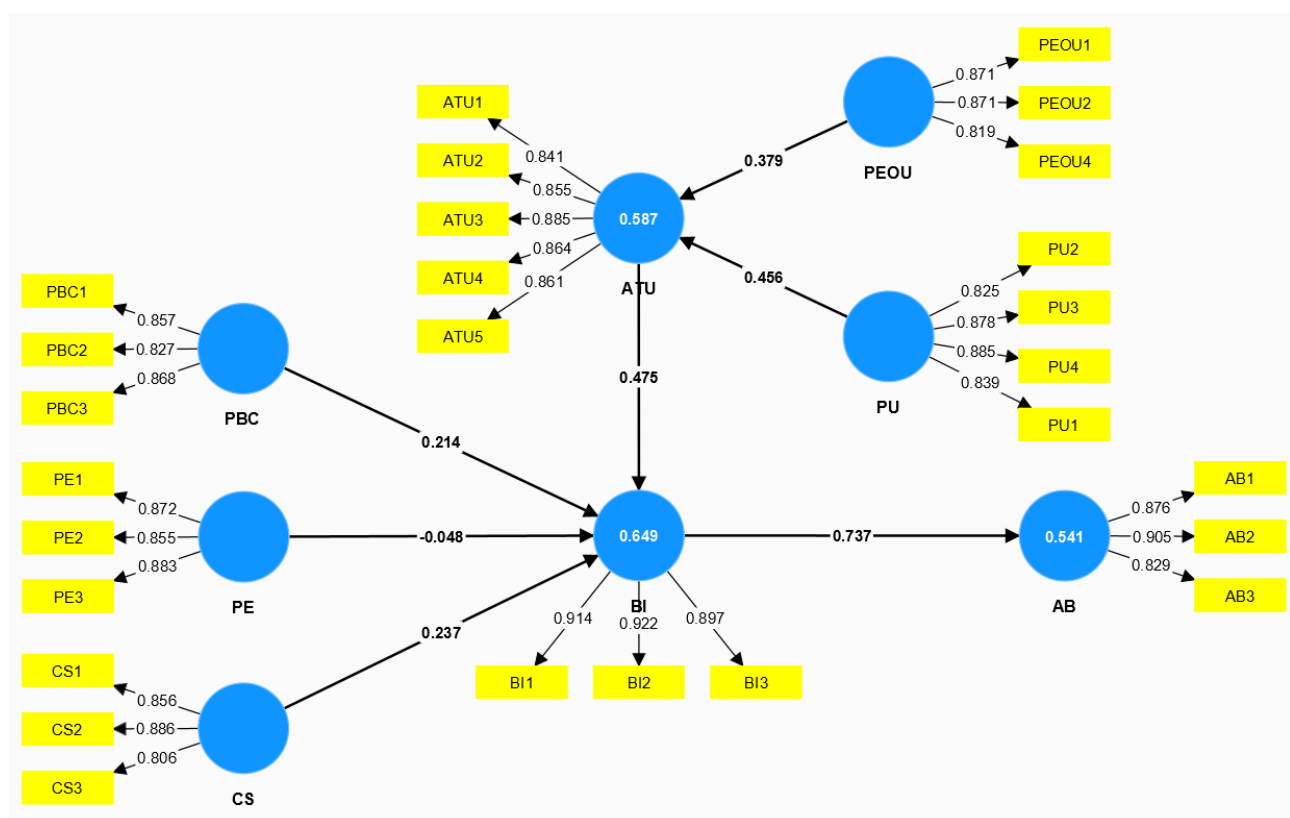


Figure 2. Structural Model Showing Path Coefficient and P-Values

Note: PBC: perceived behavioral control; PE: Perceived enjoyment; CS: Computer self-efficacy; PU: Perceived usefulness; PEOU: Perceived ease of use; ATU: Attitudes toward using AI tools; BI: Behavioral intention; AB: Actual behavior.

The indirect effect of PE → BI → AB is not significant, as the p-value is 0.457, which exceeds 0.05. In contrast, all other indirect effects are significant, with p-values below 0.05 threshold. Notably, the effect of ATU on actual behavior through behavioral intention ($\gamma = 0.350$) was the strongest (Table 11). In other words, hypotheses H9, H10, and H12 were supported. In summary, the mediation results

confirm that the strongest indirect effect was from Attitude Toward Use (ATU) to Actual Behavior (AB) via Behavioral Intention (BI), underscoring the central role of intention in linking attitude to actual behavior.

Table 11. Mediating Role of Behavioral Intention

Hypothesis	Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	p-value	Hypothesis support or reject
H9	CS -> BI -> AB	0.175	0.174	0.055	3.163	0.002	Supported
H10	PBC -> BI -> AB	0.158	0.158	0.048	3.311	0.001	Supported
H11	PE -> BI -> AB	-0.036	-0.034	0.048	0.744	0.457	Rejected
H12	ATU -> BI -> AB	0.350	0.351	0.055	6.399	0.000	Supported

The findings in Table 12 show that all inner VIF values are below the recommended threshold of 5, suggesting that multicollinearity is not an issue within the model. The adjusted R^2 values indicate that BI explains 54.1% of the variance in AB, while the predictors account for 58.7% of the variance in ATU and 64.9% in BI. These findings indicate that the model exhibits strong explanatory capability. The Q^2 values for all endogenous constructs are above zero, indicating satisfactory predictive relevance and confirming that the model possesses adequate predictive accuracy (Hair et al., 2019). Specifically, the Q^2 value for BI exceeds 0.5, indicating high predictive relevance, while the Q^2 values for ATU and AB fall between 0.25 and 0.5, indicating a moderate level of predictive relevance. Regarding effect size (f^2), the values can be interpreted according to (Cohen, 1988) as follows: BI has a strong effect on AB; PEOU and PU have moderate effects on ATU; ATU has a moderate effect on BI, while CS and PBC have small effects, and PE has no significant effect. These findings collectively support the robustness, explanatory strength, and predictive validity.

Table 12. R-Square, Cohen's f Square, Q Square and VIF values

Variable	R^2	f^2	Q^2	VIF
AB	0.541	-	0.398	-
ATU	0.587	-> BI: 0.188	0.428	-> BI: 3.454
BI	0.649	-> AB: 1.188	0.533	-> AB: 1.000
CS	-	-> BI: 0.062	0.000	-> BI: 2.634
PBC	-	-> BI: 0.053	0.000	-> BI: 2.477
PE	-	-> BI: 0.003	0.000	-> BI: 2.648
PEOU	-	-> ATU: 0.185	0.000	-> ATU: 1.895
PU	-	-> ATU: 0.268	0.000	-> 1.895

Standardized Root Mean Square Residual (SRMR) assesses the difference between the observed and predicted correlation matrices in a model. As noted by Henseler et al., 2015, an SRMR value below 0.10 is considered acceptable for model fit in PLS-SEM. Table 13 reveals that the SRMR value meets the recommended threshold, suggesting that the model achieves an acceptable fit with the observed data.

Table 13. The result of SRMR Test

	Saturated model	Estimated model
SRMR	0.061	0.094
d_ULS	1.400	3.337
d_G	0.728	0.843
Chi-square	1332.690	1412.218
NFI	0.805	0.794

5. Discussion

The findings offer meaningful insights into the determinants affecting students' intentions and actual usage of AI-powered devices for studying. As expected, perceived behavioral control (PBC), computer self-efficacy (CS), and attitude (ATU) positively influenced behavioral intention (BI), suggesting that students tend to use AI tools more readily if they feel confident in using them and perceive them as beneficial. Most of the hypothesized relationships were confirmed, except for the link between perceived enjoyment (PE) and BI, which was not significant ($p = 0.457$), resulting in the rejection of hypothesis H3. In contrast, PBC (H1), CS (H4), and attitude toward AI-powered devices (H5) all had considerable positive associations with BI.

Additionally, perceived usefulness (PU) (H6) and perceived ease of use (PEOU) (H7) positively influenced attitude, further reinforcing the adoption process. Moreover, the strong influence of behavioral intention (BI) on actual behavior (AB) ($\beta = 0.737$, $p < 0.001$) aligns with prior studies using the Theory of Planned Behavior (TPB) (Ajzen, 1991) and the Technology Acceptance Model (TAM) (Bagozzi et al., 1992), which highlight intention as a primary determinant of behavior (Maheshwari, 2021; Wang et al., 2022). Similarly, the positive effects of perceived usefulness (PU) and perceived ease of use (PEOU) on attitude (ATU) replicate earlier findings in the educational context (Naeem et al., 2023; Scherer et al., 2019; Teng et al., 2024), reinforcing the notion that functional benefits shape positive attitudes toward technology adoption.

Interestingly, the insignificant effect of perceived enjoyment (PE) on BI diverges from prior work where enjoyment was found to significantly predict intention, especially in non-academic context (Chang et al., 2023; Kim & Hall, 2019). This discrepancy suggests that in utilitarian settings like higher education, cognitive and functional motivators may outweigh hedonic factors. This view is supported by Y.-C. Chen et al., 2013, who also observed a diminished impact of enjoyment in structured learning environments. Therefore, our results add to the expanding literature suggesting that enjoyment may not serve as a universal predictor of technology adoption across all domains.

Regarding the indirect effect, the findings confirm the significant mediating role of behavioral intention (BI) in influencing actual behavior (AB), particularly for attitude (ATU), computer self-efficacy (CS), and perceived behavioral control (PBC). Specifically, the indirect effect of $ATU \rightarrow BI \rightarrow AB$ exhibited the strongest impact ($\gamma = 0.350$, $p < 0.001$), indicating that students who hold a favorable attitude toward AI-powered tools are more inclined to develop a strong intention to use them, ultimately leading to actual adoption.

Conversely, the indirect effect of perceived enjoyment (PE) $\rightarrow BI \rightarrow AB$ was not significant ($p = 0.457$), suggesting that perceived enjoyment does not meaningfully contribute to students' intention to use AI-powered tools, nor does it influence their actual behavior. This finding contrasts with some prior research where PE was a key motivator for technology adoption, especially in leisure-related

applications (e.g., gaming or social media) (Khalid, 2014; Roslan et al., 2021). However, in the academic setting, especially among Vietnamese Gen Z students, functionality, efficiency, and academic utility appear to take precedence over enjoyment.

This result may reflect the distinct characteristics of Vietnamese Gen Z students, who likely value the utilitarian benefits of AI-powered tools, such as academic performance, time efficiency, and learning outcomes, over entertainment or enjoyment factors. The swift expansion of educational technologies in Vietnam, fueled by educational demands, could explain this shift in priorities (Van Le et al., 2021; Yen et al., 2023). Moreover, cultural factors like the high value placed on academic achievement and career success may encourage a more utilitarian perspective on adopting technology, focusing on practical use rather than enjoyment. These findings suggest that, for educational technologies to be effective in such contexts, they must be designed to deliver concrete academic benefits.

The results suggest that attitude (ATU), perceived usefulness (PU), and perceived behavioral control (PBC) play significant roles in influencing students' behavioral intentions, which in turn drive actual usage. However, perceived enjoyment (PE) does not significantly impact behavioral intention, indicating that entertainment value alone may not be a strong motivator for adoption in educational contexts. Drawing from these results, several important implications arise for educators and policymakers seeking to promote the use of AI-powered tools in educational settings.

Firstly, enhancing students' perceived usefulness (PU) of AI-powered tools is crucial for encouraging their adoption in educational settings. One effective approach is to integrate these tools into daily coursework, demonstrating their practical benefits in areas such as personalized feedback, automated summarization, and AI-assisted tutoring. Additionally, educators should introduce real-life scenarios by integrating case studies and hands-on examples that showcase how AI enhances efficiency, creativity, and problem-solving skills across various academic fields. To further support adoption, universities should offer AI literacy workshops to help students understand how these tools function and how they can be leveraged for academic success.

Secondly, to drive greater adoption of AI tools, institutions should focus on leveraging perceived ease of use (PEOU) by prioritizing user-friendly designs that minimize complexity and shorten the learning curve. Additionally, integrating interactive elements such as quizzes, AI-driven gamification, or real-time feedback can improve engagement and support the effectiveness of the learning experience.

Thirdly, enhancing perceived behavioral control (PBC) is essential by reducing barriers to encourage students' adoption of AI-powered tools. Universities should negotiate institutional access to AI platforms, ensuring all students can use them without financial constraints. Additionally, providing technical support through AI help desks and step-by-step tutorials can help students overcome adoption challenges and build confidence in using these tools effectively. Equally important is the design of user-friendly AI interfaces, as institutions should prioritize AI tools that are intuitive and require minimal learning effort, making them accessible even for students with limited technical experience. Tackling these challenges enables educators to foster a more inclusive and encouraging atmosphere for the integration of AI in education.

Thirdly, leveraging computer self-efficacy (CS) is crucial for fostering greater engagement with AI-powered tools in education. Hands-on and experiential learning activities can make AI engagement more accessible and practical. Incorporating AI-driven tasks, such as simulations, guided exercises, or problem-solving applications within coursework, can help students develop familiarity and confidence in using these tools in an academic setting without feeling overwhelmed. Especially, peer-assisted learning and mentorship programs can reinforce self-efficacy by allowing students with strong AI proficiency to support their peers. Creating collaborative learning environments, such as AI

study groups or student-led tech clubs, can further encourage students to see AI as an accessible and valuable tool rather than an intimidating one.

In addition, several measures can be implemented to strengthen students' attitudes (ATU) toward AI adoption. First, emphasizing the value of AI tools in enhancing interactivity and personalization, rather than replacing traditional methods, can help shape a more positive attitude. This aligns with the study's results, which show that a positive attitude plays a key role in shaping the intention to use AI tools, ultimately driving adoption. Additionally, introducing AI tools in a low-risk environment, such as through optional assignments or extra credit tasks, allows students to experience their benefits firsthand without pressure, fostering a positive attitude by reducing initial apprehension. Finally, when educators use AI-based learning tools themselves, it builds trust and reinforces their value, encouraging students to adopt a similar attitude.

6. Conclusion

This study explored Vietnamese students' intention to adopt AI-powered study tools by integrating the Technology Acceptance Model and the Theory of Planned Behavior. The findings highlight the key roles of perceived behavioral control, computer self-efficacy, and attitude in shaping behavioral intention and actual usage. Perceived usefulness and perceived ease of use also influenced attitude, reinforcing adoption. However, perceived enjoyment did not have a meaningful effect, suggesting that students prioritize functionality over entertainment.

These results offer valuable guidance for stakeholders focused on fostering the use of AI within education. Practical implications include enhancing students' perceived usefulness of AI tools through curriculum integration, fostering self-efficacy through experiential learning, and improving accessibility through institutional support. Additionally, designing user-friendly AI platforms and addressing barriers related to perceived behavioral control can facilitate adoption.

Overall, this study contributes to the growing body of research on AI adoption in education, highlighting the unique motivations of Vietnamese Gen Z students. Future research could explore long-term adoption trends and the evolving requirements of learners. As AI-powered tools continue to shape modern education, understanding the behavioral drivers of adoption will be crucial in optimizing their effectiveness and impact. Nonetheless, this study acknowledges the limitation of online data collection, which may introduce bias from ineligible or out-of-scope participants. To mitigate this, screening questions and single-response restrictions were applied. Future studies may consider offline or mixed-method approaches to improve validity. Moreover, relying on convenience sampling constrains the generalizability of the results, which are reflective of the specific surveyed group rather than all Vietnamese university students.

Declarations

Author Contributions. T.H.N.: Literature review, conceptualization, validation, investigation, resources, writing – review and editing, supervision. D.A.T.H.: Conceptualization methodology, software, formal analysis, visualization, project administration, writing – original draft preparation. All authors have read and approved the publication of the final version of the article.

Conflicts of Interest. The authors declare no conflict of interest.

Funding. The authors received no financial support for the research and/or authorship of this article.

Ethical Approval. This study was approved by the Research Ethics Committee at Faculty of Management, School of Economics and Management, Hanoi University of Science and Technology, dated 25 September 2024. The authors further declared that the study was conducted in accordance with the highest ethical principles, including informed consent, data privacy, and confidentiality of the participant.

Data Availability Statement. Data are available from the authors upon official request.

References

- Ahmad, M. (2018). Review of the technology acceptance model (TAM) in internet banking and mobile banking. *International Journal of Information Communication Technology and Digital Convergence*, 3(1), 23–41. https://www.researchgate.net/publication/329034437_Review_of_The_Technology_Acceptance_Model_TAM_in_Internet_banking_and_Mobile_banking
- Ajzen, I. (1991). The Theory of planned behavior. *Organizational Behavior and Human Decision Processes*. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T)
- Al-Adwan, A. S., Li, N., Al-Adwan, A., Abbasi, G. A., Albelbisi, N. A., & Habibi, A. (2023). Extending the technology acceptance model (TAM) to Predict University Students' intentions to use metaverse-based learning platforms. *Education and Information Technologies*, 28(11), 15381–15413. <https://doi.org/10.1007/s10639-023-11816-3>
- Alkhatib, G., & Bayouq, S. T. (2021). A TAM-Based Model of Technological Factors Affecting Use of E-Tourism. *International Journal of Tourism and Hospitality Management in the Digital Age (IJTHMDA)*, 5(2), 50–67. <https://doi.org/10.4018/IJTHMDA.20210701.0a1>
- Arpaci, İ. (2017). The role of self-efficacy in predicting use of distance education tools and learning management systems. *Turkish Online Journal of Distance Education*, 18(1), 52–62. <https://dergipark.org.tr/tr/download/article-file/268196>
- Bagozzi, R. P., Davis, F. D., & Warshaw, P. R. (1992). Development and test of a theory of technological learning and usage. *Human Relations*, 45(7), 659–686. <https://doi.org/10.1177/001872679204500702>
- Bandura, A. (1986). Social foundations of thought and action. *Englewood Cliffs, NJ*, 1986(23–28), 2. <https://doi.org/10.4135/9781446221129.n6>
- Bashir, I., & Madhavaiah, C. (2015). Consumer attitude and behavioral intention towards Internet banking adoption in India. *Journal of Indian Business Research*, 7(1), 67–102. <https://doi.org/10.1108/JIBR-02-2014-0013>
- Bimaruci, H., Hudaya, A., & Ali, H. (2020). Model of consumer trust on travel agent online: Analysis of perceived usefulness and security on re-purchase interests (case study tiket. Com). *Dinasti International Journal of Economics, Finance & Accounting*, 1(1), 110–124. <https://doi.org/10.38035/dijefa.v1i1.227>
- Bollen, K. A. (1989). A New Incremental Fit Index for General Structural Equation Models. *Sociological Methods & Research*, 17(3), 303–316. <https://doi.org/10.1177/0049124189017003004>
- Bryan, J. D., & Zuva, T. (2021). A review of TAM and TOE framework progression and how these models integrate. *Advances in Science, Technology and Engineering Systems Journal*, 6(3), 137–145. <http://dx.doi.org/10.25046/aj060316>
- Buabeng-Andoh, C. (2018). Predicting students' intention to adopt mobile learning: A combination of theory of reasoned action and technology acceptance model. *Journal of Research in Innovative Teaching & Learning*, 11(2), 178–191. <https://doi.org/10.1108/JRIT-03-2017-0004>
- Chang, Y.-C., Enkhjargal, U., Huang, C.-I., Lin, W.-L., & Ho, C.-M. (2020). Factors affecting the Internet banking adoption. *Jurnal Ekonomi Malaysia*, 54(3), 117–131. <http://dx.doi.org/10.17576/JEM-2020-5403-9>
- Chang, Y.-W., Hsu, P.-Y., Chen, J., Shiau, W.-L., & Xu, N. (2023). Utilitarian and/or hedonic shopping–consumer motivation to purchase in smart stores. *Industrial Management & Data Systems*, 123(3), 821–842. <https://doi.org/10.1108/IMDS-04-2022-0250>

- Chao, P.-J., Hsu, T.-H., Liu, T.-P., & Cheng, Y.-H. (2021). Knowledge of and competence in artificial intelligence: Perspectives of Vietnamese digital-native students. *Ieee Access*, 9, 75751–75760. https://www.researchgate.net/publication/351730006_Knowledge_of_and_Competence_in_Artificial_Intelligence_Perspectives_of_Vietnamese_Digital_Native_Students/fulltext/60a672d145851522bceb63e0/Knowledge-of-and-Competence-in-Artificial-Intelligence-Perspectives-of-Vietnamese-Digital-Native-Students.pdf
- Chen, X., & Li, Z. (2020). Research on the behavior of college students' online tourism booking based on TAM. *Journal of Service Science and Management*, 13(01), 28. <https://doi.org/10.4236/jssm.2020.131003>
- Chen, Y.-C., LIN, Y.-C., YEH, R. C., & LOU, S.-J. (2013). *Examining factors affecting college students' intention to use web-based instruction systems: Towards an integrated model*. <http://ir.meiho.edu.tw/ir/handle/987654321/2154>
- Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research/Lawrence Erlbaum Associates*. <https://psycnet.apa.org/record/1998-07269-010>
- Chong, A. Y.-L., & Chan, F. T. (2012). Understanding the acceptance of RFID in the healthcare industry: Extending the TAM model. *Decision-Making for Supply Chain Integration: Supply Chain Integration*, 105–122. https://doi.org/10.1007/978-1-4471-4033-7_6
- Cohen, J. (1988). The effect size. *Statistical power analysis for the behavioral sciences*. Abingdon: Routledge, 77–83. <https://doi.org/10.4324/9780203771587>
- 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>
- Elkaseh, A., Wong, K. W., & Fung, C. C. (2015). A review of the critical success factors of implementing E-learning in higher education. *International Journal of Technologies in Learning*, 22(2). <https://doi.org/10.18848/2327-0144/CGP/v22i02/49160>
- Eraslan Yalcin, M., & Kutlu, B. (2019). Examination of students' acceptance of and intention to use learning management systems using extended TAM. *British Journal of Educational Technology*, 50(5), 2414–2432. <https://doi.org/10.1111/bjet.12798>
- Fathema, N., Shannon, D., & Ross, M. (2015). Expanding the Technology Acceptance Model (TAM) to examine faculty use of Learning Management Systems (LMSs) in higher education institutions. *Journal of Online Learning & Teaching*, 11(2). https://jolt.merlot.org/Vol11no2/Fathema_0615.pdf
- Fauzi, R. U. A., Juliana, J., Djakasaputra, A., Pramono, R., Antonio, F., & Purwanto, A. (2021). The role of attitude, subjective norms and usefulness on e-commerce intention and behavior. *Academic Journal of Digital Economics and Stability*, 11, 55–72. <https://doi.org/10.51699/ajdes.v11i.366>
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.2307/3151312>
- Gangwar, H., Date, H., & Ramaswamy, R. (2015). Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *Journal of Enterprise Information Management*, 28(1), 107–130. <https://doi.org/10.1108/JEIM-08-2013-0065>
- Göncz, F. D., & Tian, J. (2020). *Applying an extended theory of planned behavior model in the context of green personal care products purchase* [Doctoral dissertation, Doctoral dissertation,

Copenhagen Business School]. https://research-api.cbs.dk/ws/portalfiles/portal/66775108/1050471_Thesis_Jiaxin_Fanny.pdf

- Götz, O., Liehr-Gobbers, K., & Krafft, M. (2009). Evaluation of structural equation models using the partial least squares (PLS) approach. In *Handbook of partial least squares: Concepts, methods, and applications* (pp. 691–711). Springer. https://doi.org/10.1007/978-3-540-32827-8_30
- Ha, N., & Nguyen, T. (2019). The effect of trust on consumers' online purchase intention: An integration of TAM and TPB. *Management Science Letters*, 9(9), 1451–1460. <https://doi.org/10.5267/j.msl.2019.5.006>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer Nature. <https://link.springer.com/content/pdf/10.1007/978-3-030-80519-7.pdf>
- Ham, M., Jeger, M., & Frajman Ivković, A. (2015). The role of subjective norms in forming the intention to purchase green food. *Economic Research-Ekonomska Istraživanja*, 28(1), 738–748. <https://doi.org/10.1080/1331677X.2015.1083875>
- Hameed, M. A., & Counsell, S. (2014). Establishing relationships between innovation characteristics and IT innovation adoption in organizations: A meta-analysis approach. *International Journal of Innovation Management*, 18(01), 1450007. <https://doi.org/10.1142/S1363919614500078>
- Hayashi, A., Chen, C., Ryan, T., & Wu, J. (2004). The role of social presence and moderating role of computer self-efficacy in predicting the continuance usage of e-learning systems. *Journal of Information Systems Education*, 15(2), 139–154. https://www.researchgate.net/publication/267855475_The_Role_of_Social_Presence_and_Moderating_Role_of_Computer_Self_Efficacy_in_Predicting_the_Continuance_Usage_of_E-Learning_Systems
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43, 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In *New challenges to international marketing* (pp. 277–319). Emerald Group Publishing Limited. [https://doi.org/10.1108/S1474-7979\(2009\)0000020014](https://doi.org/10.1108/S1474-7979(2009)0000020014)
- Henseler, J., & Sarstedt, M. (2013). Goodness-of-fit indices for partial least squares path modeling. *Computational Statistics*, 28, 565–580. <https://doi.org/10.1007/s00180-012-0317-1>
- Hernández García, Á., Iglesias Pradas, S., Chaparro Peláez, J. J., & Pascual Miguel, F. J. (2011). Exploring the attitudes and intentions of non-shoppers in the acceptance of e-commerce. *Journal of Universal Computer Science*, 17(9), 1314–1328. <https://doi.org/10.3217/jucs-017-09-1314>
- Hsu, C. H., & Huang, S. (2010). *Formation of tourist behavioral intention and actual behavior*. 1–6.
- Hussein, Z. (2018). Subjective norm and perceived enjoyment among students in influencing the intention to use e-learning. *International Journal of Civil Engineering and Technology (IJCET)*, 9(13), 852–858. https://ir.uitm.edu.my/id/eprint/24783/1/AJ_ZUHAL%20HUSSEIN%20IJCET%20D%2018.pdf

- Jokar, N. K., Noorhosseini, S. A., Allahyari, M. S., & Damalas, C. A. (2017). Consumers' acceptance of medicinal herbs: An application of the technology acceptance model (TAM). *Journal of Ethnopharmacology*, 207, 203–210. <https://doi.org/10.1016/j.jep.2017.06.017>
- Kang, M. J., & Hwang, Y. C. (2022). Exploring the factors affecting the continued usage intention of IoT-based healthcare wearable devices using the TAM model. *Sustainability*, 14(19), 12492. <https://doi.org/10.3390/su141912492>
- Keržič, D., Tomaževič, N., Aristovnik, A., & Umek, L. (2019). Exploring critical factors of the perceived usefulness of blended learning for higher education students. *PloS One*, 14(11), e0223767. <https://doi.org/10.1371/journal.pone.0223767>
- Khalid, N. (2014). The role of perceived usefulness and perceived enjoyment in assessing students' intention to use LMS using 3-tum. *Global Summit on Education GSE*, 425–432. https://www.researchgate.net/publication/325681348_THE_ROLE_OF_PERCEIVED_USEFULNESS_AND_PERCEIVED_ENJOYMENT_IN_ASSESSING_STUDENTS'_INTENTION_TO_USE_LMS_USING_3-TUM
- Kim, M. J., & Hall, C. M. (2019). A hedonic motivation model in virtual reality tourism: Comparing visitors and non-visitors. *International Journal of Information Management*, 46, 236–249. <https://doi.org/10.1016/j.ijinfomgt.2018.11.016>
- Kiriakidis, S. (2015). Theory of planned behaviour: The intention-behaviour relationship and the perceived behavioural control (PBC) relationship with intention and behaviour. *International Journal of Strategic Innovative Marketing*, 3(2), 40–51. <https://doi.org/10.15556/ijsim.02.03.004>
- Kucuk, S., Baydas Onlu, O., & Kapakin, S. (2020). A model for medical students' behavioral intention to use mobile learning. *Journal of Medical Education and Curricular Development*, 7, 2382120520973222. <https://doi.org/10.1177/2382120520973222>
- Kucukusta, D., Law, R., Besbes, A., & Legohérel, P. (2015). Re-examining perceived usefulness and ease of use in online booking: The case of Hong Kong online users. *International Journal of Contemporary Hospitality Management*, 27(2), 185–198. <https://doi.org/10.1108/IJCHM-09-2013-0413>
- Maheshwari, G. (2021). Factors influencing entrepreneurial intentions the most for university students in Vietnam: Educational support, personality traits or TPB components? *Education+ Training*, 63(7/8), 1138–1153. <https://doi.org/10.1108/ET-02-2021-0074>
- Martín-García, A. V., Redolat, R., & Pinazo-Hernandis, S. (2022). Factors influencing intention to technological use in older adults. The TAM model application. *Research on Aging*, 44(7–8), 573–588. <https://doi.org/10.1177/01640275211063797>
- Mugo, D. G., Njagi, K., Chemwei, B., & Motanya, J. O. (2017). The Technology Acceptance Model (TAM) and its Application to the Utilization of Mobile Learning Technologies. *Journal of Advances in Mathematics and Computer Science*, 20(4), 1–8. <https://doi.org/10.9734/BJMCS/2017/29015>
- Naeem, M., Jawaid, S. T., & Mustafa, S. (2023). Evolution of modified TAM associated with e-banking services adoption: A systematic PRISMA review from 1975 to 2021. *Journal of Modelling in Management*, 18(3), 942–972. <https://doi.org/10.1108/JM2-10-2021-0251>
- Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B.-P. T. (2023). Ethical principles for artificial intelligence in education. *Education and Information Technologies*, 28(4), 4221–4241. <https://doi.org/10.1007/s10639-022-11316-w>

- Nguyen, H. M., & Goto, D. (2024). Unmasking academic cheating behavior in the artificial intelligence era: Evidence from Vietnamese undergraduates. *Education and Information Technologies*, 1–27. <https://doi.org/10.1007/s10639-024-12495-4>
- Nurhikmah, H., Farida, F., & Ervianti, E. (2021). The impact of computer-based Test and students' ability in computer self-efficacy on Mathematics learning outcomes. *Journal of Education Technology*, 5(4). <https://doi.org/10.23887/jet.v5i4.34942>
- Peng, D. X., & Lai, F. (2012). Using partial least squares in operations management research: A practical guideline and summary of past research. *Journal of Operations Management*, 30(6), 467–480. <https://doi.org/10.1016/j.jom.2012.06.002>
- Pivoto, D. G., De Almeida, L. F., da Rosa Righi, R., Rodrigues, J. J., Lugli, A. B., & Alberti, A. M. (2021). Cyber-physical systems architectures for industrial internet of things applications in Industry 4.0: A literature review. *Journal of Manufacturing Systems*, 58, 176–192. <https://doi.org/10.1007/s10796-022-10252-x>
- Prayudi, I. G., Sukaatmadja, I. P. G., Yasa, N. N. K., & Giantari, I. G. A. K. (2022). The role of trust in mediation the effect of perception of ease of use and perception of usefulness on intention to re-using the mobile banking service. *International Research Journal of Management, IT and Social Sciences*, 9(4), 482–493. <https://doi.org/10.21744/irjmis.v9n4.2102>
- Ringle, C. M., Sarstedt, M., Mitchell, R., & Gudergan, S. P. (2020). Partial least squares structural equation modeling in HRM research. *The International Journal of Human Resource Management*, 31(12), 1617–1643. <https://doi.org/10.1080/09585192.2017.1416655>
- Roslan, R., Ayub, A. F. M., Ghazali, N., & Zulkifli, N. N. (2021). The influence of perceived ease of use, perceived usefulness, social influence, and perceived enjoyment towards continuance intention in using a gamified e-quiz mobile application. *Journal of Institutional Research South East Asia*, 19(2). https://openurl.ebsco.com/EPDB%3Agcd%3A16%3A14459456/detailv2?sid=ebsco%3Aplink%3Ascholar&id=ebsco%3Agcd%3A154771726&crl=c&link_origin=www.google.com
- Saadé, R. G., & Kira, D. (2009). Computer anxiety in e-learning: The effect of computer self-efficacy. *Journal of Information Technology Education: Research*, 8(1), 177–191. <https://doi.org/10.28945/3386>
- Salloum, S. A., Alhamad, A. Q. M., Al-Emran, M., Monem, A. A., & Shaalan, K. (2019). Exploring students' acceptance of e-learning through the development of a comprehensive technology acceptance model. *Ieee Access*, 7, 128445–128462. <https://ieeexplore.ieee.org/document/8825866>
- Saparudin, M., Rahayu, A., Hurriyati, R., & Adib Sultan, M. (2020). The influence of trust, perceived usefulness, and perceived ease upon customers' attitude and intention toward the use of mobile banking in Jakarta. *Journal of Theoretical and Applied Information Technology*, 98(17), 3584–3594. <https://www.jatit.org/volumes/Vol98No17/14Vol98No17.pdf>
- Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education*, 128, 13–35. <https://doi.org/10.1016/j.compedu.2018.09.009>
- Shah Alam, S., & Mohamed Sayuti, N. (2011). Applying the Theory of Planned Behavior (TPB) in halal food purchasing. *International Journal of Commerce and Management*, 21(1), 8–20. <https://doi.org/10.1108/10569211111111676>

- Shalender, K., & Sharma, N. (2021). Using extended theory of planned behaviour (TPB) to predict adoption intention of electric vehicles in India. *Environment, Development and Sustainability*, 23(1), 665–681. <https://doi.org/10.1007/s10668-020-00602-7>
- Simsek, A. (2011). The relationship between computer anxiety and computer self-efficacy. *Contemporary Educational Technology*, 2(3), 177–187. <https://files.eric.ed.gov/fulltext/ED542215.pdf>
- Steinbauer, G., Kandlhofer, M., Chklovski, T., Heintz, F., & Koenig, S. (2021). A Differentiated Discussion About AI Education K-12. *KI - Künstliche Intelligenz*, 35(2), 131–137. <https://doi.org/10.1007/s13218-021-00724-8>
- Su, C.-Y., & Chiu, C.-H. (2021). Perceived enjoyment and attractiveness influence Taiwanese elementary school students' intention to use interactive video learning. *International Journal of Human-Computer Interaction*, 37(6), 574–583. <https://doi.org/10.1080/10447318.2020.1841423>
- Tam, W. V., Le, K. N., Tran, C. N., & Wang, J. Y. (2018). A review on contemporary computational programs for Building's life-cycle energy consumption and greenhouse-gas emissions assessment: An empirical study in Australia. *Journal of Cleaner Production*, 172, 4220–4230. <https://doi.org/10.1016/j.jclepro.2017.11.130>
- Tan, M., & Teo, T. S. (2000). Factors influencing the adoption of Internet banking. *Journal of the Association for Information Systems*, 1(1), 5. <https://doi.org/10.17705/1jais.00005>
- Taylor, S., & Todd, P. (1995). Understanding household garbage reduction behavior: A test of an integrated model. *Journal of Public Policy & Marketing*, 14(2), 192–204. <https://doi.org/10.1177/074391569501400202>
- Teng, Y.-M., Wu, K.-S., & Kuo, F.-J. (2024). Virtual reality tourism: Intention to use mediated by perceived usefulness, attitude and desire. *Tourism Review*. <https://doi.org/10.1108/TR-02-2024-0133>
- Teng, Y.-M., Wu, K.-S., & Liu, H.-H. (2015). Integrating altruism and the theory of planned behavior to predict patronage intention of a green hotel. *Journal of Hospitality & Tourism Research*, 39(3), 299–315. <https://doi.org/10.1177/1096348012471383>
- Troise, C., O'Driscoll, A., Tani, M., & Prisco, A. (2021). Online food delivery services and behavioral intention—a test of an integrated TAM and TPB framework. *British Food Journal*, 123(2), 664–683. <https://doi.org/10.1108/BFJ-05-2020-0418>
- Uoc, T. M. (2023). Transforming educational methods of political theory before impact of ChatGPT in Vietnam today. *Conhecimento & Diversidade*, 15(38), 1–11. <https://doi.org/10.18316/rcd.v15i38.11023>
- Urton, K., Wilbert, J., Krull, J., & Hennemann, T. (2023). Factors explaining teachers' intention to implement inclusive practices in the classroom: Indications based on the theory of planned behavior. *Teaching and Teacher Education*, 132, 104225. <https://doi.org/10.1016/j.tate.2023.104225>
- Ustadi, M. N., & Mat, C. R. C. (2023). The Evolution of Theory of Reasoned Action (TRA) and Theory of Planned Behavior (TPB). In *Technologies and Trends in the Halal Industry*. [https://books.google.com.vn/books?hl=en&lr=&id=DVTcEAAAQBAJ&oi=fnd&pg=RA1-PT26&dq=The+Evolution+of+Theory+of+Reasoned+Action+\(TRA\)+and+Theory+of+Planned+Behavior+\(TPB\)+To+Predict+Whether+a+Person+Intends+to+Do+Something,+Researchers+Need+to+Know&ots=oXKNZMEHNR&sig=spN2q8-](https://books.google.com.vn/books?hl=en&lr=&id=DVTcEAAAQBAJ&oi=fnd&pg=RA1-PT26&dq=The+Evolution+of+Theory+of+Reasoned+Action+(TRA)+and+Theory+of+Planned+Behavior+(TPB)+To+Predict+Whether+a+Person+Intends+to+Do+Something,+Researchers+Need+to+Know&ots=oXKNZMEHNR&sig=spN2q8-)

ilZVh2rqnl4T6uwEafvQ&redir_esc=y#v=onepage&q=The%20Evolution%20of%20Theory%20of%20Reasoned%20Action%20(TRA)%20and%20Theory%20of%20Planned%20Behavior%20(TPB)%20To%20Predict%20Whether%20a%20Person%20Intends%20to%20Do%20Something%20C%20Researchers%20Need%20to%20Know&f=false

- Van Le, H., Tran, M. T. T., & Vo, V.-L. (2021). The Vietnamese educators and students' perception towards high school teacher training activities according to competency-based education. *JETT*, 12(4), 112–118. <https://doi.org/10.47750/jett.2021.12.04.015>
- Wang, K., van Hemmen, S. F., & Criado, J. R. (2022). The behavioural intention to use MOOCs by undergraduate students: Incorporating TAM with TPB. *International Journal of Educational Management*, 36(7), 1321–1342. <https://doi.org/10.1108/IJEM-11-2021-0446>
- Weng, F., Yang, R.-J., Ho, H.-J., & Su, H.-M. (2018). A TAM-based study of the attitude towards use intention of multimedia among school teachers. *Applied System Innovation*, 1(3), 36. <https://doi.org/10.3390/asi1030036>
- Yang, X. (2019). Accelerated move for AI education in China. *ECNU Review of Education*, 2(3), 347–352. <https://doi.org/10.1177/2096531119878590>
- Yen, P. H., Thi, N. A., Thuy, P. T., Tra, N. H., & Thu, H. T. A. (2023). Assessment strategies in outcome-based education: Preferences and practices among university lecturers in Vietnam. *International Journal of Learning, Teaching and Educational Research*, 22(10), 416–432. <https://doi.org/10.26803/ijlter.22.10.23>
- Yuen, K. F., Cai, L., Qi, G., & Wang, X. (2021). Factors influencing autonomous vehicle adoption: An application of the technology acceptance model and innovation diffusion theory. *Technology Analysis & Strategic Management*, 33(5), 505–519. <https://doi.org/10.1080/09537325.2020.1826423>
- Zaremohzzabieh, Z., Ismail, N., Ahrari, S., & Samah, A. A. (2021). The effects of consumer attitude on green purchase intention: A meta-analytic path analysis. *Journal of Business Research*, 132, 732–743. <https://doi.org/10.1016/j.jbusres.2020.10.053>

About the Contributor(s)

Thanh Huong Nguyen, PhD, is a lecturer at the Faculty of Management and Economics, Hanoi University of Science and Technology (HUST), Vietnam. She earned her PhD in Business Administration with a specialization in Human Resource Management from HUST, Vietnam. Her research focuses on human resource management, leadership, organizational behavior, and sustainable development.

Email: huong.nguyenthanh4@hust.edu.vn

ORCID: <https://orcid.org/0000-0003-1447-0305>

Do Anh Tu Ha, is an undergraduate student in Management Information Systems at the Faculty of Mathematics and Informatics, Hanoi University of Science and Technology (HUST), Vietnam. His main research interests include business administration, mathematics, and algorithm design as applied to information systems.

Email: Tu.HDA237491@sis.hust.edu.vn

ORCID: <https://orcid.org/0009-0005-9945-4727>

Publisher's Note: The opinions, statements, and data presented in all publications are solely those of the individual author(s) and contributors and do not reflect the views of Universitepark, EDUPIJ, and/or the editor(s). Universitepark, the Journal, and/or the editor(s) accept no responsibility for any harm or damage to persons or property arising from the use of ideas, methods, instructions, or products mentioned in the content.

Appendix I.

Table A1. Research Measurement

1. Perceived usefulness (PU)

- PU1 I find that using AI-powered tools significantly improves my academic performance.
- PU2 I find that AI-powered tools are more time-efficient than traditional methods.
- PU3 I find that AI-powered tools make my learning process easier.
- PU4 In general, I find that AI-powered tools offer many benefits for my learning

2. Perceived ease of use (PEOU)

- PEOU1 I find AI-powered tools clear and easy to understand.
- PEOU2 I find it easy to make AI-powered tools do what I need.
- PEOU3 I do not need much effort to interact with AI-powered tools.
- PEOU4 In general, I find AI-powered tools simple to use.

3. Perceived behavioral control (PBC)

- PBC1 I believe I can successfully utilize any AI-powered tools.
- PBC2 I believe I have full control over the situation when using AI-powered tools.
- PBC3 I believe I possess sufficient resources to utilize AI-powered tools whenever needed
- PBC4 I have sufficient resources to utilize AI-powered tools, even if it requires higher costs.
- PBC5 I have the right to choose whether to use AI-powered tools or not.

4. Perceived enjoyment (PE)

- PE1 I find using AI-powered tools interesting.
- PE2 Using AI-powered tools has sparked my imagination and creativity.
- PE3 Using AI-powered tools stimulates my curiosity and desire to explore and learn.

5. Attitudes toward using AI (ATU)

- ATU1 I have a positive view of using AI tools.
- ATU2 Using AI-powered tools is a smart choice.
- ATU3 I support the use of AI-powered tools.

ATU4 I believe that using AI-powered tools will help me make a positive difference.

ATU5 Overall, I enjoy learning with AI-powered tools.

6. Subjective norm (SN)

SN1 Most people important to me think that I should use AI-powered tools.

SN2 My friends advise me to use AI-powered tools.

SN3 Many of my friends use AI-powered tools.

SN4 I feel the need to use AI-powered tools to avoid falling behind.

SN5 I believe that the university supports the use of AI-powered tools within certain limits.

7. Computer self-efficacy (CS)

CS1 I am confident in my self-learning ability when using AI-powered tools.

CS2 I am confident in my ability to effectively use AI-powered tools to complete my tasks.

CS3 I am confident in using AI-powered tools with only online instructions.

8. Behavioral intention (BI)

BI1 I intend to use AI-powered tools in the long term.

BI2 I am willing to use AI-powered tools.

BI3 I will frequently use AI-powered tools in my studies and work in the future.

9. Actual behavior (AB)

AB1 I have experience using AI-powered tools in my studies and work.

AB2 I frequently use AI-powered tools in my studies and work.

AB3 In most cases, I mainly rely on AI-powered tools rather than traditional learning methods.
