Factors Affect the Intentions to Use Artificial Intelligence Tools and the Actual Use of Students in Higher Educational Institutions

Thai Thi Thuy Oanh[1]

Eastern International University

Correspondence: oanh.thai@eiu.edu.vn

Received: 17/04/2024; Revised: 25/07/2024; Accepted: 31/07/2024

Abstract

This study investigated the roles of technology readiness in shaping university students' perceptions of usefulness and ease of use, and how these perceptions influence their intentions and actual use of AI tools. A total of 343 valid responses were analyzed using the SPSS (version 27) and Smart-PLS (version 4.1.1.0). The findings reveal that among the four elements of technology readiness, optimism and innovativeness positively affect perceived usefulness and ease of use, while discomfort and insecurity had a negative effect. Furthermore, perceived usefulness, perceived ease of use, subject norms, and perceived behavioral control positively impacted the intentions to use AI tools and led to positive actual use. The results suggest that students view AI as a supportive tool in their study. These insights could help universities enhance the effectiveness of teaching and studying, and guide technology companies in developing strategies that align with user readiness and behavioral intentions.

Keywords: *artificial intelligence, intention, technology readiness*

1. Introduction

Artificial intelligence (AI) is a revolutionary technology that has significantly accelerated the process of digital transformation in various industries through recent rapid breakthroughs (Duan et al., 2019). AI has been acknowledged for its unprecedented ability to influence our lives and our world, both in positive and negative ways (Dignum, 2023). It excels at processing large amounts of data and making accurate predictions (Wheatley and Hervieux, 2019). AI can improve users' productivity, economy, and decision-making processes (Hayani et al., 2021).

The utilization of AI in higher educational institutions (HEIs) has experienced rapid growth over the past five years, accompanied by a simultaneous increase in the availability of new AI technologies (Chu et al., 2022). Chen et al. (2020) discusses AI's advantages and capabilities for educators and students in higher education. Many AI tools, including Grammarly, ChatGPT, Quillbot, Jenni AI, Ivy Chatbot, Cognii, Symbolab, Knowji, Otter.AI, and Speechify have been employed in a range of domains such as business contexts, educational institutions, and personal use (Cortez et al., 2024). Vietnamese companies stand to

[1] MBA Student, International University - Vietnam National University HCMC, Vietnam National University HCMC

gain significantly from the widespread use of AI (Nguyen and Tran, 2019). AI is projected to make a significant economic impact, contributing trillions of US dollars to the world economy each year. Vietnam is predicted to emerge as a leading force in AI development in Southeast Asia, earning the title of an "AI dragon" and further advancing the progress of AI in the region year.

Various computer-assisted instruction AI tools, such as Grammarly, ChatGPT, and Quillbot, have been employed (Cortez et al., 2024). A comprehensive knowledge of AI tools used in Vietnamese higher education still needs to be improved. Therefore, the goal of this study is to fully comprehend which factors affect the intentions to use AI tools and the actual use among students in HEIs.

2. Theoretical Foundation and Research Hypotheses

AI is commonly characterized as machines that demonstrate aspects of human intellectual ability (Huang and Rust, 2018). Therefore, firms must comprehend the process of implementing AI technologies to enhance management practices and product offerings (Kumar et al., 2019). Enabling students to learn independently with the support of AI technology will significantly benefit them (Alzahrani, 2023).

Through digital educational technologies, it is now feasible to assess a student's level of comprehension and mastery of new knowledge and abilities and promptly rectify the learning process, enhancing the adaptability of education (Kuleto et al., 2022). The discipline of AI can potentially enhance and broaden teaching and learning in higher education (Roy et al., 2022). Cope et al. (2021) examined the implementation of AI at universities and presented insights on the prospects of technology integration in education. AI in education can revolutionize the learning process and foster the development of students' creative and analytical abilities (Ouyang and Jiao, 2021).

2.1. The influence of technology readiness (TR) on the perceived ease of use (PE) and the perceived usefulness (PU)

Technology readiness refers to an individual's inclination to adopt or utilize new technology to achieve their objectives in their personal or professional life (Sudaryanto et al., 2023). It has four dimensions: optimism, innovation, insecurity, and discomfort (Parasuraman, 2000).

Discomfort (DC) refers to the technical fear and nervousness experienced by customers towards technology (Parasuraman, 2000). It refers to uneasiness experienced while utilizing a particular technology (Roy et al., 2022). These arise because of individuals' evolving reluctance to embrace new technology (Roy et al., 2022).

People who experience significant DC find embracing and adopting new technology challenging (Roy et al., 2022). Typically, feeling uncomfortable might cause people to be hesitant about using new technology, which can have a negative impact on their willingness to adopt it (Pillai et al., 2020). Kim and Chiu (2019) have shown that DC has a detrimental impact on the PE of new technology. Thus, a hypothesis was proposed:

H1: DC negatively influences the PE of AI tools in HEIs.

DC signifies people's adverse sentiment towards the new technology (Cambre and Cook, 1985). Kim and Chiu (2019) indicate that DC has a detrimental impact on the PU. Thus, a hypothesis was proposed:

H2: DC negatively influences the PU of AI tools in HEIs.

Insecurity (ISC) arises when people lack competence in understanding the benefits of technology, leading to doubt and uncertainty (Roy et al., 2022). It refers to individuals' need for more confidence or trust in using new technology, which prevents them from fully taking advantage of its potential (Kamble et al., 2019).

The presence of ISC has a detrimental impact on the acceptance and implementation of novel technological advancements (Parasuraman and Colby, 2001). The current collection of academic research on the acceptance of new technology demonstrates that ISC has a negative effect on PE (Kim and Chiu, 2019). Consumers who lack belief are uncertain about how to use technology (Godoe and Johansen, 2012). Thus, a hypothesis was proposed:

H3: ISC negatively influences the PE of AI tools in HEIs.

People experiencing ISC would exhibit less reliance on technology and believe that technology will inevitably fail during vital periods (Kotler and Armstrong, 2014; Parasuraman and Colby, 2001). ISC is a significant deterrent to the use of technology (Tsikriktsis, 2004). ISC has an adverse effect on the perceived utility of emerging technologies (Kim and Chiu, 2019). ISC mainly stems from a deficiency in confidence towards technology, hence exerting a detrimental impact on adopting technology (Parasuraman and Colby, 2001). Thus, a hypothesis was proposed:

H4: ISC negatively influences the PU of AI tools in HEIs.

Optimism (OP) about technology is a perspective that has a positive belief in the capabilities of technology, asserting that it provides individuals with greater control, adaptability, and effectiveness in their daily lives (Parasuraman and Colby, 2001). Optimistic customers are more inclined to embrace new technologies, viewing them as effective and reliable (Lu et al., 2012). Therefore, customers with an optimistic perception are more inclined to have a good attitude towards new technologies (Godoe and Johansen, 2012).

OP pertains to individuals' optimistic perspective towards technology, as it offers them increased efficiency, flexibility, and control (Pillai et al., 2020). It refers to an individual's inclination to actively pursue and use newly available technologies in the marketplace (Liljander et al., 2006). Customers with a sense of OP towards technology exhibit a positive mindset when adopting new technological advancements and are more open to embracing such innovations (Tsikriktsis, 2004; Parasuraman, 2000). PE is influenced by OP (Ali et al., 2015; Kim and Chiu, 2019; Chen et al., 2020). Thus, a hypothesis was proposed:

H5: OP positively influences the PE of AI tools in HEIs.

OP leads consumers to believe that new technology offers increased adaptability, enhanced efficiency, and greater command over daily chores (Parasuraman and Colby, 2015). Therefore, many believe technology benefits them (Tsikriktsis, 2004). Prior research has identified the impact of OP on the perception of usefulness (Ali et al., 2015; Chen et al., 2018; Godoe and Johansen, 2012). Thus, a hypothesis was proposed:

H6: OP positively influences the PU of AI tools in HEIs.

Innovativeness (IN) is the consumer's willingness to engage in adventurous behaviors when using technology (Kotler and Armstrong, 2014). People with a forward-thinking perspective may perceive technology as easily applicable to a specific purpose (Godoe and Johansen, 2012).

A forward-thinking consumer may perceive technology as easily applicable for a specific purpose (Liljander et al., 2006). Previous research recognized the impact of IN on PE (Ali et al., 2015; Chen et al., 2018; Kim and Chiu, 2019). Thus, a hypothesis was proposed:

H7: IN positively influences the PE of AI tools in HEIs.

Consumers with an inventive mentality towards technology typically have a strong understanding of technology and find learning new technologies engaging (Parasuraman and Colby, 2001). These proactive consumers perceive technology as valuable and easy to navigate (Kim and Chiu, 2019) and Ali et al. (2015) confirms the positive relationship between IN and PU. Thus, a hypothesis was proposed:

H8: IN positively influences the PU of AI tools in HEIs.

2.2. The influence of PE on the intention (IT) to use AI tools

PE refers to the extent to which an individual believes that utilizing a specific system would require minimal effort (Davis, 1989). Individuals are inclined to contemplate a PE if they perceive it as uncomplicated and demanding minimal exertion (Roy et al., 2022).

The PE directly impacts IT adoption (Kalinic and Marinkovic, 2016). Investigation into the adoption of technology demonstrates that PE impacts the IT to utilize technology (Kim and Chiu, 2019). Thus, a hypothesis was proposed:

H9: The PE positively influences the IT to use AI tools in HEIs.

2.3. The influence of PU on the IT to use AI tools

PU refers to the extent to which an individual believes that utilizing a specific system would improve their job performance (Davis, 1989). It refers to an individual's own view that a particular technology has the potential to enhance their professional growth and advancement (Roy et al., 2022).

Customers are more likely to accept technology when they perceive it as beneficial for enhancing performance (Davis, 1989). The studies on adopting new technology also demonstrate the impact of PU on IT use (Kim and Chiu, 2019; Liu et al., 2019). Thus, a hypothesis was proposed:

H10: The PU positively influences the IT to use AI tools in HEIs.

2.4. The influence of subjective norms (SN) on the IT to use AI tools

SN refer to an individual's impression of the beliefs and opinions of others who are important to them regarding what they should or should not do (Roy et al., 2022). SN reflects an individual's beliefs of how their reference groups will see them if they engage in a specific behaviour (Al-Swidi et al., 2014).

A study on SN discovered that SN is a significant determinant that positively impacts users' inclination to adopt technology (Wheatley and Hervieux, 2019). The influence of SN on the IT to engage in a specific behavior has been highlighted as a positive element (Momani and Jamous, 2017). SN exerts the most significant impact on IT (Roy et al., 2022). SN has been found to impact individuals' opinions of the usefulness of technology (Xie et al., 2017). Hayani et al. (2021) recognized the strong influence of SN on the inclination to use new technology. Thus, a hypothesis was proposed:

H11: The SN positively influences IT to use AI tools in HEIs.

2.5. The influence of perceived behavior control (PBC) on the IT to use AI tools

PBC is individuals' perception regarding their capability to successfully carry out a specific conduct (Roy et al., 2022). It refers to how individuals perceive ease or difficulty in performing a specific behavior. It quantifies an individual's subjective conviction of having authority over a specific action or behavior (Yakubu et al., 2023).

Consumers' intention towards behaviors is positively influenced by PBC (Siqueira et al., 2022). It substantially impacts consumers when it comes to adopting innovations like AI (Pourmand et al., 2020). It has proven to be an effective indicator of the likelihood of people adopting technology in different situations (Kumar et al., 2019). PBC is an accurate indicator of their capacity to accomplish the behaviour, and when combined with IT, it can be used to predict actual behavior (Verma and Sinha, 2018). Prior studies have shown inconclusive findings about the correlation between PBC and IT (Gupta and Arora, 2020). Thus, a hypothesis was proposed:

H12: The PBC positively influences the IT to use AI tools in HEIs.

2.6. The influence of IT on the actual use AI tools

IT indicates whether customers will continue or end their relationship with the service provider (Zeithaml et al., 1996). Favorable intentions refer to customers expressing a positive word of mouth, a desire to repurchase, and loyalty (Zeithaml et al., 1996). IT can be seen as customers

developing a favorable perception of the company's products and services (Amin and Zahora, 2013). IT can be seen as a strong motivation and readiness to participate in a specific activity (Chai et al., 2022). Thus, a hypothesis was proposed:

H13: The IT use of AI tools positively influences the actual use of it in HEIs.

Based on the literature above, a conceptual framework was proposed:

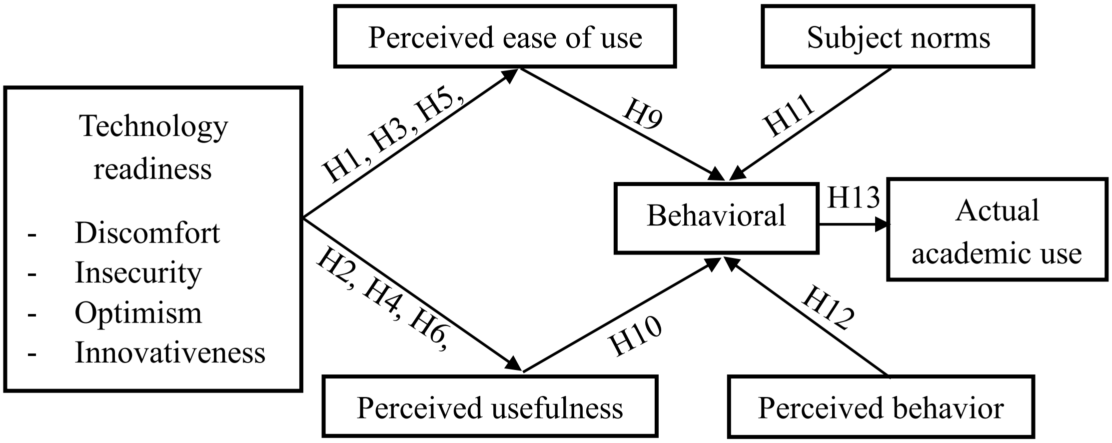

Figure 1. The proposed research model

3. Methodology

Before the final questionnaire was released, a pre-test should be done to improve the survey questions (Burns and Bush, 2000). A pilot study was conducted in individuals with a small, representative group of respondents including 30 students and professionals. The objective is to assess whether any statements are too challenging to understand due to uncommon language, grammar, or structure (Colton and Covert, 2015). The results from the pre-test indicate that the questionnaires are sufficiently accurate to be used for data collection in the survey.

The survey questionnaire was separated into two parts: the initial section contained variables such as sex, the study year, and frequency of usage. The next part aimed to examine the formation and assessment of each crucial factor of the study. The size of the sample, which varies between about 200 and 300, indicates the rough and constant reliability of the findings (Comrey and Lee, 2013). The research targets to gather information from 350 students using AI tools as a supportive tool for their study process in HCM city.

The author contacts students studying universities at HCM city through online platforms. Participants may immediately complete the questions upon obtaining the link to the questionnaire via emails and social media platforms such as Facebook and Zalo. The author contacted directly to students in universities to ask them to conduct the survey. Besides that, the students who have already conducted the survey helped the author to spread out the purpose of this study and gave the survey link to other students to participate in the survey. Moreover, the author used social media networks to raise help of students conducting the survey. The target population of the study mainly from Hong Bang University, University of Economics Ho Chi Minh City, International University - Vietnam National University HCMC, Hoa Sen University, Van Lang University and HCMC University of Technology and Education which were both private and public universities.

343 participants yielded precise and adequate findings for statistical analysis. The legitimate answers will be gathered, while the unqualified ones, indicating that

individuals have not yet encountered AI tools and those who provided similar ratings, will be discarded. The sampling quota was a selective technique for screening appropriate applicants for the sample. The measurement of every element was conducted utilizing a five-point Likert scale, which ranged from 1 (indicating strongly disagree) to 5 (indicating strongly agree). The result was entered to analyzed using SPSS in order to examine the information about demographic and perform an EFA analysis. Subsequently, the study used PLS-SEM to evaluate the adequacy of the fit of the model and the study model. PLS-SEM is a set of methods utilize to analyze the relationships between a set of continuous and discrete independent variables and dependent variables (Ullman and Bentler, 2012). Structural equation modeling allows for the concurrent estimate all variables in each model. It enables the estimation of the causal connection of latent concepts by using indicators that integrate assessment and the structure of the theoretical framework (Bowen and Guo, 2012). The research utilized PLS-SEM to examine the proposed framework (Hair et al., 2011). The research contains 41 sample elements and 343 efficient observations, exceeding the required minimum number of samples for Structural Equation Modeling (SEM).

The evaluation of all concepts was conducted using a multi-item assessment that was modified from preexisting research. The measurement of TR was based on 16 constructs divided into four categories: OP, IN, DC, and ISC, which were adopted from Parasuraman and Colby (2015). The measurement of PE and PU was based on 8 constructs, which were adopted from Davis et al. (1989) and Bhattacherjee (2000). The measurement of SN and PBC was based on 7 constructs adopted from Kamble et al. (2019). The measurement of IT and actual academic use were based on 10 constructs adopted from Prasetyo et al. (2020).

4. Results and Discussion

4.1. Demographic analysis

The sample demographics accurately reflected the distribution of gender, the study year and uses frequency. Of the 343 individuals who participated in the survey, 49.3% were female, 46.1% were male, and 4.7% were other. The participants consist of a relatively equal distribution of genders. Regarding the study year, 24.5% are freshmen, 18.7% are in the second year, 26.2% are in the third year, 27.4% are in the fourth year and 3.2% are in others. As the results of the study year illustrated, the students who were in the third year and the fourth year had a dominant percent. It could contribute to the accuracy of the answers of these students owing to their heavy workload in their study year. They might need more help from AI tools which could support them to handle their study. Regarding the university, the survey was conducted in six universities, both public and private. 46.65% of the respondents from Hong Bang University (13.70%), Hoa Sen University (19.24%), and Van Lang University (13.70%). The rest of the students (53.35%) came from International University - Vietnam National University HCMC (22.45%), University of Economics Ho Chi Minh City (15.74%), and HCMC University of Technology and Education (15.16%). This figure could provide the appropriate result.

From the figure above, the demographic data are accurate enough to represent the study population.

4.2. Measurement model

The factor loadings for these elements ranged from 0.710 to 0.925, which is among the satisfactory threshold determined by Hulland (1999). Thus, while examining the factors that account for other characteristics, it was noted that these variables had sufficient variety. The measurement of the item was considered accurate. According to Hair et al. (2011), VIF values need to be below 5 to avoid problems related to collinearity. The research's Variance Inflation Factor (VIF) met the required range value (Table 1).

This research investigated the internal consistency and reliability of the constructs by utilizing the composite reliability (CR) method (Jöreskog, 1971). The indicator results represented different levels of acceptance. Drolet and Morrison (2001) determined that the most effective degree of dependability ranged from 0.7 to 0.9, whereas acceptable degrees of reliability were between 0.6 and 0.7. The model fit value has met the preset range values (Hair et al., 2011), it could be inferred that the assessment elements effectively reflect their underlying latent construct. Afterwards, the measurement model was used to assess the convergent and discriminant validity of the measurement scales. This analysis determined each of the variables had a CR that above 0.7. The research's reliability and internal consistency were established for each component (Netemeyer et al., 2003). This research showed a Cronbach's alpha over 0.7 is sufficient. In order to assess the convergent validity of a concept, it is necessary for the average extracted variation (AVE) to be more than 0.5, as stated by Hair et al. (2011). The average value (AVE) in this experiment ranged from 0.549 to 0.801, indicating that there is convergent validity (Table 1).

Table 1. Constructs' properties, items' loadings and VIF

Constructs	Variables	Code	Factor loadings	Cronbach's alpha	Average variance extracted (AVE)	VIF
Technology readiness	Optimism	OP1	0.781	0.837	0.671	1.723
		OP2	0.891			2.412
		OP3	0.835			1.903
		OP4	0.764			1.626
	Innovativeness	IN1	0.780	0.824	0.654	1.671
		IN2	0.823			1.725
		IN3	0.833			1.987
		IN4	0.797			1.638
	Discomfort	DC1	0.816	0.899	0.769	2.204
		DC2	0.895			3.121
		DC3	0.868			2.599
		DC4	0.925			3.888
	Insecurity	ISC1	0.878	0.910	0.789	2.769
		ISC2	0.909			3.247
		ISC3	0.849			2.306
		ISC4	0.914			3.462

Constructs	Variables	Code	Factor loadings	Cronbach's alpha	Average variance extracted (AVE)	VIF
Perceived usefulness		PU1	0.885	0.917	0.801	2.973
		PU2	0.924			4.369
		PU3	0.853			2.369
		PU4	0.917			3.952
Perceived ease of use		PE1	0.818	0.790	0.614	1.788
		PE2	0.765			1.527
		PE3	0.780			1.579
		PE4	0.771			1.524
Subject norms		SN1	0.809	0.745	0.661	1.559
		SN2	0.813			1.375
		SN3	0.818			1.594
Perceived behavior control		PBC1	0.799	0.841	0.677	1.759
		PBC2	0.853			1.959
		PBC3	0.786			1.668
		PBC4	0.851			2.113
Intention		IT1	0.711	0.793	0.549	1.485
		IT2	0.710			1.418
		IT3	0.744			1.476
		IT4	0.712			1.453
		IT5	0.821			1.898
Actual academic use		AT1	0.798	0.863	0.646	1.816
		AT2	0.806			2.047
		AT3	0.759			1.958
		AT4	0.858			2.425
		AT5	0.796			2.167

The researcher utilized two methods to evaluate discriminant validity: the Fornell-Larcker criteria and the Heterotrait-Monotrait Ratio of Correlations (HTMT). The Fornell-Larcker criteria states that the square roots of the Average Variance Extracted (AVEs) have more statistical significance compared to the cross-construct correlations (Roldán and Sánchez-Franco, 2012). The data presented in "Error! Reference source not found." indicates that nearly all the variables demonstrate satisfactory discriminant validity (Table 2).

Table 2. Fornell-Larcker criterion

	AT	DC	IN	ISC	IT	OP	PBC	PE	PU	SN
AT	0.804									
DC	-0.413	0.877								
IN	0.387	-0.459	0.809							
ISC	-0.432	0.417	-0.375	0.888						
IT	0.496	-0.445	0.487	-0.478	0.741					
OP	0.558	-0.405	0.440	-0.481	0.535	0.819				
PBC	0.412	-0.406	0.434	-0.461	0.526	0.478	0.823			

PE	0.477	-0.495	0.481	-0.464	0.574	0.477	0.470	0.784		
PU	0.526	-0.426	0.545	-0.428	0.562	0.540	0.518	0.535	0.895	
SN	0.534	-0.407	0.491	-0.482	0.511	0.502	0.495	0.479	0.538	0.813

Given that this research focuses on evaluating theory rather than evaluating a measurement scale, it was determined that the findings were not compromised. Additionally, the Heterotrait-Monotrait Ratio of Correlations (HTMT) from Henseler et al. (2015) indicates that all the values are below the predetermined threshold of 0.9. Thus, the assessment model exhibits enough accuracy to proceed with the following phase of the research, which involves analyzing the structural model (Table 3).

Table 3. Heterotrait-monotrait ratio (HTMT) - Matrix

	AT	DC	IN	ISC	IT	OP	PBC	PE	PU	SN
AT										
DC	0.465									
IN	0.452	0.534								
ISC	0.484	0.461	0.430							
IT	0.591	0.524	0.597	0.563						
OP	0.650	0.465	0.524	0.547	0.654					
PBC	0.481	0.471	0.519	0.533	0.639	0.571				
PE	0.579	0.587	0.591	0.546	0.722	0.574	0.577			
PU	0.588	0.469	0.625	0.468	0.656	0.611	0.589	0.628		
SN	0.667	0.493	0.622	0.590	0.660	0.640	0.621	0.620	0.650	

4.3. Structural model

The study then used CB-SEM in SmartPLS 4.1.1.0 to test the model fit. The result showed that the CMIN/DF = 1.587 (<3), GFI = 0.865 (>0.8), CFI = 0.946 (>0.9), TLI = 0.939 (>0.9), RMSEA = 0.041 (<0.05) which may be determined the measurement model had been truly appropriate according to Hair et al. (2011).

Structural equation modeling (SEM) was utilized in the last stage to examine and validate the hypotheses (Suhr, 2006). A p-value below 0.05 indicates a significant association between the variables (Hu and Bentler 1990; Hair et al., 2006). Hence, the study accepted all the hypotheses. The results were aligned with Kallweit et al. (2014), Parasuraman and Colby (2015), Ali et al. (2015), Godoe and Johansen (2012), Chen et al. (2018), Roy et al. (2022), and Cortez et al. (2024).

The result shows that **OP** (β=0.194; t=3.671; p=0.000), the **IN** (β=0.215; t=3.785; p=0.000) positively impacts the **PE**. The **DC** (β=-0.239; t=2.644; p=0.008), the **ISC** (β=-0.190; t=3.744; p=0.000) negatively impacts the **PE**. The **OP** (β=0.298; t=5.892; p=0.000), the **IN** (β=0.319; t=6.910; p=0.000) positively impacts the **PU**. The **DC** (β=-0.109; t=2.084; p=0.037), the **ISC** (β=-0.120; t=2.451; p=0.014) negatively impacts the **PU**. The **PE** (β=0.287; t=3.728; p=0.000), the **PU** (β=0.221; t=4.128; p=0.000), the

SN (β=0.155; t=3.125; p=0.002) and the **PBC** (β=0.200; t=3.676; p=0.000) positively impacts the **IT**. The **IT** (β=0.496; t=8.334; p=0.000) positively impacts actual academic use (Table 4).

Table 4. Summary of the findings

H	Relationships	O	M	STDEV	T	P	Decisions
1	DC → PE	-0.239	-0.238	0.090	2.644	0.008	Accepted
2	DC → PU	-0.109	-0.110	0.052	2.084	0.037	Accepted
3	ISC → PE	-0.190	-0.188	0.051	3.744	0.000	Accepted
4	ISC → PU	-0.120	-0.117	0.049	2.451	0.014	Accepted
5	OP → PE	0.194	0.194	0.053	3.671	0.000	Accepted
6	OP → PU	0.298	0.296	0.050	5.892	0.000	Accepted
7	IN → PE	0.215	0.213	0.057	3.785	0.000	Accepted
8	IN → PU	0.319	0.318	0.046	6.910	0.000	Accepted
9	PE → IT	0.287	0.279	0077	3.728	0.000	Accepted
10	PU → IT	0.221	0.221	0.054	4.128	0.000	Accepted
11	SN → IT	0.155	0.157	0.050	3.125	0.002	Accepted
12	PBC → IT	0.200	0.203	0.054	3.676	0.000	Accepted
13	IT → AT	0.496	0.496	0.059	8.334	0.000	Accepted

Hypothesis: H, Original sample: O, Sample mean: M, Standard deviation: STDEV, T statistics (|O/STDEV|): T, P values: P

4.4. Discussion

The results illustrate that DC negatively influences PE and PU which is aligned with the study of Kallweit et al. (2014). ISC negatively affects PE and PU, the same as previous studies (Parasuraman and Colby, 2015; Godoe and Johansen, 2012). The outcomes indicate that OP positively influences PE and PU, which aligns with Ali et al. (2015). IN also positively affects PE and PU, which was proved in prior studies (Godoe and Johansen, 2012; Ali et al., 2015). PE and PU positively influence the intention of using AI tools, which was aligned with Chen et al. (2018). SN and PBC also positively influence the intention of using AI tools, which was aligned with Roy et al. (2022). The intention of using AI tools positively influences actual academic use in higher educational institutions, which was aligned with Cortez et al. (2024).

Students who experience higher levels of DC may be particularly receptive to embracing AI tools, as automation eliminates the desire for learning and navigating complex technological processes. Besides that, ISC in students' perception is a barrier that restricts them from utilizing AI tools in their study. Using these tools raises concerns about their perception of leaked personal information. Moreover, AI tools might provide inaccurate information or make mistakes, affecting the students' productivity. Students who have an optimistic view about the development of AI and take advantage of its innovation could perceive its usefulness and ease of use positively. These attitudes could help them exploit maximumly the upsides of AI tools.

Students typically prefer technologies that exhibit high performance and take minimal effort to operate. Moreover, when they are aware of the benefits of AI tools from their perspective or directly from their surroundings, their intention of using them increases and as a result, their actual use of these tools also increases.

4.5. Theoretical implications

The study contributed to the comprehensive understanding of AI tools in higher educational institutions. Among the four elements of TR, OP and IN positively affect PE and PU, while DC and ISC have adverse effects. TR has both upside and downside impacts on PE and PE. People can strengthen the positive elements to take advantage of technology and narrow the effect of DC and ISC to increase the technology's usefulness and ease of use. The research also highlighted the positive correlation between four factors: PE, PU, SN, and PBC on IT. The results of this study significantly contributed to the understanding of factors impacting customers' intentions in the context of using academic AI tools. The outcome also confirmed the positive relationship between IT and actual academic use.

4.6. Managerial implications

AI tools can help students at HEIs perform their academic tasks. From the perspective of students, they can take advantage of AI tools to enhance and boost their productivity in the learning process. HEIs should also apply more technological adoption for the learners to create an advanced environment for both teaching and learning. Moreover, technological developers can see AI applications as a potential market to penetrate due to the positive intention to use and the actual use of the customers. The study's outcomes can be seen as evidence that firms can develop and expand their businesses in the context of AI academic applications.

5. Conclusion

This study highlighted the essential role of TR in students' intention to use AI tools and their actual use. This research also proved the positive roles of PE, PU, SN and PBC in IT. The outcomes as evidence of students to enhance their study effectiveness through utilizing AI as supportive tools. The university council and the board of presidents can also improve teaching and learning effectiveness by encouraging students to use AI tools and creating an advanced learning environment for students to study with technologies. Enterprises can also take advantage of developing more advanced educational applications due to the increase of potential customers in the future.

This study contains several limitations. First, the study collected data mainly from Ho Chi Minh City, which may limit the research inference. Hence, future studies should expand the study sample from other provinces. Second, the study examined the uses of AI tools among students who may not utilize all the advantages of AI tools in teaching. Thus, future studies should consider taking samples from lecturers and learners in higher educational institutions. Third, the following research can be considered carried out at various educational institutions, not only in universities.

Conflict of Interest

The authors declare no conflict of interest.

References

Al-Swidi, A., Huque, S. M. R., Hafeez, M. H., and Shariff, M. N. M. (2014). The role of subjective norms in theory of planned behavior in the context of organic food consumption. *British Food Journal*, *116*(10): 1561-1580. https://doi.org/10.1108/BFJ-05-2013-0105

Ali, H., Ali, T., Matar, Z., and Jawad, F. (2015). Citizens' acceptance and readiness towards adopting e-participation tools in kingdom of Bahrain. *International Journal for Infonomics*, *8*(2): 1029-1036. https://doi.org/10.20533/iji.1742.4712.2015.0121

Alzahrani, L. (2023). Analyzing Students' Attitudes and Behavior Toward Artificial Intelligence Technologies in Higher Education. *International Journal of Recent Technology and Engineering (IJRTE)*, *11*(6): 65-73. http://www.doi.org/10.35940/ijrte.F7475.0311623

Amin, M., and Nasharuddin, S. Z. (2013). Hospital service quality and its effects on patient satisfaction and behavioural intention. *Clinical Governance: An International Journal*, *18*(3): 238-254. https://doi.org/10.1108/CGIJ-05-2012-0016

Bhattacherjee, A. (2000). Acceptance of e-commerce services: the case of electronic brokerages. In *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, 30*(4): 411-420. DOI: 10.1109/3468.852435.

Bowen, N. K., and Guo, S. (2011). *Structural equation modeling*. Oxford University Press.

Burns, A. C., and Bush, R.F. (2000). *Marketing Research* (3rd ed.). Prentice Hall.

Cambre, M. A., and Cook, D. L. (1985). Computer anxiety: Definition, measurement, and correlates. *Journal of Educational Computing Research*, *1*(1): 37-54. https://doi.org/10.2190/fk5l-092h-t6yb-pyba

Chai, C. S., Chiu, T. K., Wang, X., Jiang, F., and Lin, X. F. (2022). Modeling Chinese secondary school students' behavioral intentions to learn artificial intelligence with the theory of planned behavior and self-determination theory. *Sustainability*, *15*(1): 605.

Chen, L., Chen, P., and Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE access*, *8*: 75264-75278.

Chen, Y. M., Hsu, T. H., and Lu, Y. J. (2018). Impact of flow on mobile shopping intention. *Journal of Retailing and Consumer Services*, *41*: 281-287.

Chu, H. C., Hwang, G.-H., Tu, Y.-F., and Yang, K.-H. (2022). Roles and research trends of artificial intelligence in higher education: A systematic review of the top 50 most-cited articles. *Australasian Journal of Educational Technology*, *38*(3): 22-42. https://doi.org/10.14742/ajet.7526

Colton, D., and Covert, R. W. (2007). *Designing and constructing instruments for social research and evaluation*. John Wiley & Sons.

Comrey, A. L., and Lee, H. B. (2013). *A first course in factor analysis*. Psychology Press. https://doi.org/10.4324/9781315827506

Cope, B., Kalantzis, M., and Searsmith, D. (2021). Artificial intelligence for education: Knowledge and its assessment in AI-enabled learning ecologies. *Educational Philosophy and Theory*, *53*(12): 1229-1245.

Cortez, P. M., Ong, A. K. S., Diaz, J. F. T., German, J. D., and Jagdeep, S. J. S. S. (2024). Analyzing Preceding factors affecting behavioral intention on communicational artificial intelligence as an educational tool. *Heliyon, 10*(3): e25896. https://doi.org/10.1016/j.heliyon.2024.e25896

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

Dignum, V. (2023). Responsible Artificial Intelligence: Recommendations and Lessons Learned. In Eke, D.O., Wakunuma, K., Akintoye, S. (eds) *Responsible AI in Africa: Challenges and Opportunities*. *Social and Cultural Studies of Robots and AI*. Palgrave Macmillan, Cham. https://doi.org/10.1007/978-3-031-08215-3_9

Drolet, A. L., and Morrison, D. G. (2001). Do we really need multiple-item measures in service research? *Journal of Service Research*, *3*(3): 196–204. https://doi.org/10.1177/109467050133001

Duan, Y., Edwards, J. S., and Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International Journal of Information Management*, *48*: 63-71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Godoe, P., and Johansen, T. S. (2012). Understanding adoption of new technologies: Technology readiness and technology acceptance as an integrated concept. *Journal of European Psychology Students*, *3*(1): 38-52. https://doi.org/10.5334/jeps.aq

Gupta, K., and Arora, N. (2020). Investigating consumer intention to accept mobile payment systems through unified theory of acceptance model: An Indian perspective. *South Asian Journal of Business Studies*, *9*(1): 88-114. https://doi.org/10.1108/SAJBS-03-2019-0037

Hair, J. F., Anderson, R. E., Tatham, R. L., and Black, W. C. (2006). *Multivariate data analysis with readings* (Vol. 6). New York, NY: Pearson Prentice Hall.

Hair, J. F., Ringle, C. M., and Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2): 139-152. https://doi.org/10.2753/MTP1069-6679190202

Hayani, A., Sari, E. A., and Sukiman, S. (2021). Artificial Intelligence Librarian as Promotion of IAIN

Lhokseumawe Library in the Revolutionary Era 4.0. *Journal of Robotics and Control (JRC)*, *2*(2): 88-93. https://doi.org/10.18196/jrc.2258

Henseler, J., Ringle, C. M., and 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

Hu, L. T., and Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1): 1-55. https://doi.org/10.1080/10705519909540118

Huang, M. H., and Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, *21*(2): 155-172. https://doi.org/10.1177/1094670517752459

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic management journal*, *20*(2): 195-204.

Jöreskog, K. G. (1971). Statistical analysis of sets of congeneric tests. *Psychometrika*, *36*(2): 109-133. https://doi.org/10.1007/BF02291393

Kalinic, Z., and Marinkovic, V. (2016). Determinants of users' intention to adopt m-commerce: an empirical analysis. *Information Systems and e-Business Management*, *14*: 367-387. https://doi.org/10.1007/s10257-015-0287-2

Kallweit, K., Spreer, P., and Toporowski, W. (2014). Why do customers use self-service information technologies in retail? The mediating effect of perceived service quality. *Journal of Retailing and Consumer Services*, *21*(3): 268-276. https://doi.org/10.1016/j.jretconser.2014.02.002

Kamble, S., Gunasekaran, A., and Arha, H. (2019). Understanding the Blockchain technology adoption in supply chains-Indian context. *International Journal of Production Research*, *57*(7): 2009-2033. https://doi.org/10.1080/00207543.2018.1518610

Kim, T. and Chiu, W. (2019). Consumer acceptance of sports wearable technology: the role of technology readiness. *International Journal of Sports Marketing and Sponsorship, 20*(1): 109-126. https://doi.org/10.1108/IJSMS-06-2017-0050

Kotler, P., and Armstrong, G. (2014). *Principles of marketing*. Pearson education.

Kuleto, V., Bucea-Manea-Țoniş, R., Bucea-Manea-Țoniş, R., Ilić, M. P., Martins, O. M., Ranković, M., and Coelho, A. S. (2022). The potential of blockchain technology in higher education as perceived by students in Serbia, Romania, and Portugal. *Sustainability*, *14*(2): 749.

Kumar, V., Rajan, B., Venkatesan, R., and Lecinski, J. (2019). Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review*, *61*(4): 135-155. https://doi.org/10.1177/0008125619859317

Liljander, V., Gillberg, F., Gummerus, J., and Van Riel, A. (2006). Technology readiness and the evaluation and adoption of self-service technologies. *Journal of Retailing and Consumer Services*, *13*(3): 177-191. https://doi.org/10.1016/j.jretconser.2005.08.004

Lu, J., Wang, L., and Hayes, L. A. (2012). How do technology readiness, platform functionality and trust influence C2C user satisfaction? *Journal of Electronic Commerce Research*, *13*(1): 50-69.

Momani, A. M., and Jamous, M. (2017). The evolution of technology acceptance theories. *International Journal of Contemporary Computer Research (IJCCR)*, *1*(1): 51-58. https://www.researchgate.net/publication/316644779

Netemeyer, R. G., Bearden, W. O., and Sharma, S. (2003). *Scaling procedures: Issues and applications*. Sage Publications.

Nguyen, P. V., and Tran, H. X. (2019). Behavioural intention to accept mobile wallet: An empirical study of a developing country perspective. *International Journal of Information Systems and Supply Chain Management*, *12*(5): 93-107.

Ouyang, F., and Jiao, P. (2021). Artificial intelligence in education: The three paradigms. *Computers and Education: Artificial Intelligence*, *2*: 100020. https://doi.org/10.1016/j.caeai.2021.100020

Parasuraman, A. (2000). Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research*, *2*(4): 307-320. https://doi.org/10.1177/109467050024001

Parasuraman, A., and Colby, C. L. (2001). *Techno-ready marketing: How and why your customers adopt technology*. The Free Press.

Parasuraman, A., and Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of Service Research*, *18*(1): 59-74. https://doi.org/10.1177/1094670514539730

Pillai, R., Sivathanu, B., and Dwivedi, Y. K. (2020). Shopping intention at AI-powered automated retail stores (AIPARS). *Journal of Retailing and Consumer Services*, *57*: 102207. https://doi.org/10.1016/j.jretconser.2020.102207

Pourmand, G., Doshmangir, L., Ahmadi, A., Noori, M., Rezaeifar, A., Mashhadi, R., Aziminia, R., Pourmand, A. and Gordeev, V. S. (2020). An application of the theory of planned behavior to self-care in patients with hypertension. *BMC Public Health*, *20*: 1290. https://doi.org/10.1186/s12889-020-09385-y

Prasetyo, Y. T., Castillo, A. M., Salonga, L. J., Sia, J. A., and Seneta, J. A. (2020). Factors affecting perceived effectiveness of COVID-19 prevention measures among

Filipinos during enhanced community quarantine in Luzon, Philippines: Integrating Protection Motivation Theory and extended Theory of Planned Behavior. *International journal of infectious diseases*, *99*: 312-323.

Roldán, J. L., and Sánchez-Franco, M. J. (2012). Variance-based structural equation modeling: Guidelines for using partial least squares in information systems research. In M. Mora, O. Gelman, A. Steenkamp, and M. Raisinghani (Eds.), *Research methodologies, innovations and philosophies in software systems engineering and information systems* (pp. 193-221). IGI global.

Roy, R., Babakerkhell, M. D., Mukherjee, S., Pal, D., and Funilkul, S. (2022). Evaluating the intention for the adoption of artificial intelligence-based robots in the university to educate the students. *Ieee Access*, *10*: 125666-125678.

Siqueira, M. S. S., Nascimento, P. O., and Freire, A. P. (2022). Reporting Behaviour of People with Disabilities in Relation to the Lack of Accessibility on Government Websites: Analysis in the light of the Theory of Planned Behaviour. *Disability, CBR & Inclusive Development*, *33*(1): 52-68. https://doi.org/10.47985/dcidj.475

Sudaryanto, M. R., Hendrawan, M. A., and Andrian, T. (2023). The effect of technology readiness, digital competence, perceived usefulness, and ease of use on accounting students' artificial intelligence technology adoption. In *E3S Web of Conferences* (Vol. 388, p. 04055). EDP Sciences.

Suhr, D. D. (2006). *Exploratory or confirmatory factor analysis?*. SAS Institute.

Tsikriktsis, N. (2004). A technology readiness-based taxonomy of customers: A replication and extension. *Journal of service research*, *7*(1): 42-52.

Ullman, J. B., and Bentler, P. M. (2013). Structural equation modeling. In J. A. Schinka, W. F. Velicer, and I. B. Weiner (Eds.), *Handbook of psychology: Research methods in psychology* (2nd ed., pp. 661-690). John Wiley & Sons.

Verma, P., and Sinha, N. (2018). Integrating perceived economic wellbeing to technology acceptance model: The case of mobile based agricultural extension service. *Technological forecasting and social change*, *126*: 207-216. https://doi.org/10.1016/j.techfore.2017.08.013

Wheatley, A., and Hervieux, S. (2019). Artificial intelligence in academic libraries: An environmental scan. *Information Services & Use*, *39*(4), 347-356. https://doi.org/10.3233/isu-190065

Xie, Q., Song, W., Peng, X., and Shabbir, M. (2017). Predictors for e-government adoption: integrating TAM, TPB, trust and perceived risk. *The Electronic Library*, *35*(1): 2-20. https://doi.org/10.1108/EL-08-2015-0141

Yakubu, A. S., Yagana, A. A., and Umar, S. I. Y. (2023). Investigating librarians' intention to use artificial intelligence for effective library service delivery: A partial least square-structural equation modeling-based approach. *Dutse Journal of Pure and Applied Sciences*, *9*(1b): 1-14.

Zeithaml, V. A., Berry, L. L., and Parasuraman, A. (1996). The behavioral consequences of service quality. *Journal of Marketing*, *60*(2): 31-46.