MULTIDISCIPLINARY SCIENCE JOURNAL

RESEARCH ARTICLE
Published Online: November 14, 2024
https://doi.org/10.31893/multiscience.2025275

AI-assisted learning: An empirical study on student application behavior

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Abstract In the wake of the fourth industrial revolution, artificial intelligence is gaining momentum and is widely applied in various aspects of life, particularly education. This study investigates the factors influencing students' use of artificial intelligence (AI) in learning, focusing on students at Ho Chi Minh City University of Industry. The research uses a combination of the technology acceptance model and the theory of planned behavior to examine the relationships between subjective norms, image, job relevance, output quality, result demonstrability, self-efficacy, anxiety, perceived playfulness, perceived enjoyment, perceived ease of use, perceived usefulness, and behavioral intention. Combining these technological models brings new insights into the context of AI that can support or hinder user behavior through bias. The results were then analyzed based on the least squares linear structural model, with 390 students participating in the survey using the stratified sampling approach. The study found that perceived ease of use and usefulness are the most significant factors influencing students' intention to use AI in learning. Subjective norms also play an essential role in shaping students' image and intention to use AI. The research also highlights the importance of self-efficacy, perceived enjoyment, playfulness, output quality, result demonstrability, and job relevance in influencing students' perceptions and use of AI. The findings of this study underscore the need for educational institutions to create a supportive environment that encourages students to use AI in learning. In contrast, AI technology creators need to focus on simplifying the user experience to make AI tools more accessible and easy to use. These practical recommendations of the research can guide policy and design decisions in the field of educational technology. Finally, in place of a conclusion, the study also aims to open up further approaches for AI platforms in academia.

Keywords: artificial intelligence, TAM, learning support, self-efficacy

1. Introduction

Artificial intelligence (AI) may seem new, but it has been around for a long time. According to Pan (2016), AI is the ability of machines such as computers to understand, learn, and think like humans do. Simply put, AI can simulate human intelligence in areas such as learning and working. According to Mata et al. (2018), AI technology is a field of science that seeks to solve problems by simulating human biological thought processes such as reasoning, learning, and self-correction. AI is a computer system designed to interact with the world through intelligent capabilities and behaviors that we consider human (Luckin & Holmes, 2016). In an era of ever-evolving advanced technology, artificial intelligence (AI), a branch of computer science that aims to create intelligent machines that can imitate human behavior, has become an indispensable part of human life. Technological advancements have led to innovations in disease diagnosis and treatment, healthcare, and knowledge acquisition (Algerafi et al., 2023). AI has had a profound impact and is a driving force behind the socioeconomic development of nations. AI is an intelligent tool that helps students acquire knowledge in education. Students can use AI to search for reference materials, and they can also use virtual assistants to solve their questions (Hien, 2020). The role of AI in education became more evident during the COVID-19 pandemic when direct interactions were limited and traditional classroom learning was disrupted. AI enables the continuation of teaching and learning through virtual classrooms. This adaptability extends beyond school systems; online courses and personalized learning applications have also become popular. For example, Duolingo, an application that provides language learning exercises, has leveraged AI to create a personalized learning program that adapts to each student's pace and level on the basis of their performance. This is just one example of how AI is improving and innovating traditional education, making it more convenient and advanced (Roy et al., 2022).

However, not all students are willing to accept and apply AI to their learning. Hien (2020) reported that many students, especially those majoring in business, are less receptive to new technologies and less enthusiastic about applying AI to their learning. According to Em et al. (2024), in a survey, only 10.8% of students at Ho Chi Minh City National University used the paid version of Chat GPT, a chatbot developed by OpenAI and launched in November 2022, for their studies. This figure reflects

 Received: September 17, 2024 | Accepted: October 28, 2024

the problem of very few students taking full advantage of the capabilities and features of chatbots to solve their learning challenges. The main reasons for students not using AI for learning include their need for more basic AI searching and usage skills, their need to learn how to use AI effectively, and their need to trust the AI's ability to provide accurate and reliable information.

Recent global research, including studies by Saari et al. (2022), Hien (2020), Algerafi et al. (2023), and Roy et al. (2022), has acknowledged the importance of AI and its limitations in student use. Our research, however, takes a novel approach by combining the concerns of perceived ease of use and perceived usefulness. We also highlight the role of subjective norms, a factor that has not been fully explored in previous studies, to understand its linear relationship with image, perceived usefulness, and direct influence on the behavioral intention to use. Additionally, we delve into the causal factors that drive perceived usefulness and ease of use, offering a fresh perspective on these concepts. Therefore, this study was conducted to identify the factors affecting students' use of AI. Therefore, we propose managerial implications or solutions to enhance the use of AI in learning for students at Ho Chi Minh City University of Industry. To achieve the above research objectives, the following sections present the theoretical basis for building hypotheses and forming a research model. The study then uses data analysis methods and techniques to determine the results.

2. Literature Review

2.1. Related Theory

An overview of the literature shows that researchers mainly use models and theories such as the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975), the theory of planned behavior (TPB) (Ajzen, 1991), the technology acceptance model TAM1 (Davis, 1989), TAM2 (Venkatesh & Davis, 2000), TAM3 (Venkatesh & Bala, 2008), the combined model of TAM and TPB (C-TAM-TPB) (Taylor & Todd, 1995), and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). These models and theories are important because they provide a structured framework to understand and predict technology acceptance in educational contexts, thus guiding the development and implementation of technology in education. Fishbein and Ajzen's (1975) theory of reasoned action (TRA) suggests that behavioral intentions lead to behavior and are determined by an individual's attitudes and the influence of subjective norms. Attitudes and subjective norms are essential to determining any individual's behavioral intentions. The theory of planned behavior (TPB), which evolved from TRA, was first proposed by (Fishbein & Ajzen, 1975). The TPB provides a practical conceptual framework to address the complexity of human social behavior. The theory incorporates several critical concepts in the social and behavioral sciences while defining these concepts in a way that allows for the prediction and understanding of specific behaviors in specific contexts. TAM is one of the most widely used theories in the study of user behavior with technology. TAM, developed by Davis (1989), aims to assess the factors influencing employees' acceptance and use of technology in the workplace. Davis and his research team identified three main variables that determine technology acceptance: (1) perceived usefulness (PU), (2) perceived ease of use (PEU), and (3) attitudes toward technology (ATT). However, owing to the limitations of the TAM's explanatory power, a new model, TAM2, was developed (Venkatesh & Davis, 2000). This model assumes that work goals and outcomes when using technology form the basis for perceived usefulness (PU). However, TAM2 focuses only on the determinants of PUs. The limitations of the TAM and TAM2 in fully explaining technology acceptance in education, especially in the context of social factors, highlight the need for a more comprehensive research model. By 2003, a more developed research model that investigated the social factors influencing technology adoption intentions emerged. Venkatesh et al.'s (2003) UTAUT explained users' intentions to use information systems and subsequent usage behavior. This theory proposes four main factors: 1) performance expectancy, 2) effort expectancy, 3) social influence, and 4) facilitating conditions. This study was developed by reviewing and reinforcing the structure of eight models that previous studies have used to explain information system usage behavior.

UTAUT theory suggests that technology use is determined by behavioral intention. The UTAUT model was developed by Venkatesh et al. (2003) with four main factors: performance expectancy, effort expectancy, social influence, and facilitating conditions. In addition, there are moderating factors such as age, gender, experience, and willingness to use. The UTAUT can be considered a more comprehensive model built on eight models: the theory of reasoned action (TRA), the technology acceptance model (TAM), the motivational model (MM), the theory of planned behavior (TPB), the model of computer use (MPCU), and innovation diffusion theory (IDT). Venkatesh & Bala (2008) proposed the TAM3 model, which further integrates the determinants of perceived ease of use (PEOU). These include individual differences, system characteristics, social influences, and facilitating conditions such as PEOU and perceived usefulness (PU) determinants. User experience was added to TAM3 as a moderator in the relationships between computer anxiety and PEOU, PEOU, and PU, as well as PEOU and behavioral intention (BI). Previously, Taylor and Todd (1995) integrated the Technology Acceptance Model and the Theory of Planned Behavior to add subjective norms and perceived behavioral control to the Technology Acceptance Model, forming the combined C-TAM-TPB model. The C-TAM-TPB combines predictors from the TAM and TPB, such as attitudes toward behavior, subjective norms, perceived behavioral control, and perceived usefulness, in the study of people's evaluations of information technology use.

2.2. Hypotheses and research model

2.2.1. Subjective Norms

Fishbein (1976) defined subjective norms as referring to people's opinions and attitudes toward their social circle, including friends, family members, and coworkers. Subjective norms are also defined as the extent to which an individual perceives that most people important to them think they should or should not use the system. TAM2 hypothesizes that subjective norms positively correlate with image (Venkatesh & Davis, 2000). This link is supported by previous studies confirming that image significantly impacts behavioral intentions if individuals follow the advice of their coworkers to maintain their personal status and image within the group (Chassin et al., 1990; Pfeffer, 1992). Saari et al. (2022) studied the adoption of social robots in the workplace and reported that subjective norms significantly influence image. In addition, Venkatesh et al. (2003) reported a positive correlation between subjective norms and perceived usefulness. In 2008, Venkatesh and Bala reaffirmed that subjective norms and perceived usefulnessfulness are positively correlated.

Park et al. (2012) also reported that subjective norms significantly influence perceived usefulness when mobile devices are used for learning. Furthermore, Venkatesh et al. (2003) and Park et al. (2012) reported positive correlations between subjective norms and behavioral intentions. Subjective norms can significantly influence a person’s behavior and play an essential role in forming behavioral intentions (Saari et al., 2022). In 2012, Park et al. noted that subjective norms positively and significantly impact behavioral intention in the use of mobile devices for learning. Therefore, the hypotheses are as follows:

H1.1: Subjective norms have a positive effect on image.

H1.2: Subjective norms have a positive effect on perceived usefulness.

H1.3: Subjective norms have a positive effect on behavioral intention*.*

2.2.2. Image

Image has been defined by Moore & Benbasat (1991) as the degree to which a person feels that using an innovation is perceived to improve his or her status in the social system. The study of Saari et al. (2022) confirmed the positive influence of images on perceived usefulness. In the study by Algerafi et al. (2023), the positive correlation between image and perceived usefulness is shown by students' willingness to use AI-based robots in learning because they perceive that using these technologies will improve their reputation. Furthermore, Setiyani (2021) reported that image significantly positively impacted the perceived usefulness of Google Drive in online learning as a storage medium throughout the COVID-19 pandemic. This enables the student to present himself or herself as a professional in the use of technology. Therefore, hypothesis H2 is stated as follows:

H2: Image has a positive effect on perceived usefulness.

2.2.3. Job Relevance

Job relevance is people's perception of the target technology's degree of fit or applicability to their work (Venkatesh & Bala, 2008). This concept is further supported by Travaglini et al. (2023), who argue that when a function is considered essential to a particular field of work, individuals are likely to perceive the benefits of that function and intend to use the product. Two studies by Venkatesh & Davis (2000) and Venkatesh & Bala (2008) confirmed that job relevance positively correlates with perceived usefulness. Similarly, Ucha (2023) emphasized the importance of relevance in determining the perceived usefulness of a course system, with job relevance identified as a critical determinant in the TAM. Furthermore, Kim et al. (2009) reported that the job relevance of information technology in auditing significantly impacts the usefulness of the technology. Hypothesis H3 is stated as follows:

H3: Job relevance has a positive effect on perceived usefulness.

2.2.4. Output Quality

The output quality is the extent to which an individual believes that the system performs its job tasks well. Output quality positively impacts perceived usefulness (Venkatesh & Davis, 2000). The findings of (Algerafi et al., 2023) also indicate that output quality has a positive influence on perceived usefulness, which is consistent with the findings of Lee et al. (2023). This is demonstrated by students' belief that AI-based robots will produce high-quality results. Similarly, in research to enhance the user experience, the output quality of GPS sports watches intensely impacts consumers' perceived usefulness (Yuan et al., 2021). Therefore, Hypothesis H4 is stated as follows:

H4: Output quality has a positive effect on perceived usefulness.

2.2.5. Result Demonstrability

Result demonstrability is the degree to which an individual believes that the outcomes of using a system are tangible, observable, and communicable (Moore & Benbasat, 1991). Venkatesh & Davis (2000) acknowledge that result demonstrability directly influences perceived usefulness. Early adopters perceive robots as valid when they can tell others about the robot and communicate how to use it, and the results from using the robot are precise (Saari et al., 2022). Y. Chen et al. (2023) revealed that AI chatbots supporting students do an excellent job of helping with student learning, underscoring the importance of AI chatbots in educational technology. In sports, Yuan et al. (2021) reported that GPS watches are also helpful because of the positive results they bring to users, highlighting the relevance of result demonstrability in sports technology. Additionally, in agriculture, Soodan et al. (2024) affirmed result demonstrability as a determinant of the intention to use agricultural advisory mobile applications. Hypothesis H5 is proposed as follows:

H5: Result demonstrability has a positive effect on perceived usefulness.

2.2.6. Self-Efficacy

Self-efficacy is the extent to which an individual believes that they can perform a task/job using a computer (Compeau & Higgins, 1995a, 1995b). It refers to an individual's confidence in his or her ability to perform a specific task (Ozturk et al., 2016). Venkatesh & Davis (2000) acknowledge that self-efficacy directly influences perceived ease of use. The research results of Algerafi et al. (2023) confirmed the positive impact of self-efficacy on perceived ease of use. The results indicate that students believe that they can operate and receive support from AI-based robots in education. The report by Saari et al. (2022) also points out the same. Huang & Ren (2020) reported that exercise self-efficacy moderates the continued use of mobile fitness apps among Chinese users.

Similarly, Rizun & Strzelecki (2020) studied the impact of self-efficacy on student acceptance of the transition from on-campus to remote learning in higher education during the COVID-19 pandemic in Poland. Similar results have also been reported for online learning (Salloum et al., 2019) and the adoption of mobile wallets in the hospitality industry (Lew et al., 2020). Therefore, hypothesis H6 is proposed as follows:

H6: Self-efficacy has a positive effect on perceived ease of use.

2.2.7. Anxiety

Anxiety is the level of apprehension or even fear an individual experiences when faced with the prospect of using a computer (Venkatesh, 2000). Anxiety is described as the level of discomfort an individual experiences when faced with the prospect of using technology (Venkatesh & Bala, 2008). Each individual's mental state influences mainly the fear of using AI-based robots in terms of their willingness and ability to embrace technology (Salimon et al., 2018). The negative correlation between anxiety and perceived ease of use has been demonstrated through research by the following authors: Venkatesh (2000); Salimon et al. (2018). The TAM3 model of Venkatesh & Bala (2008) demonstrated that a person's anxiety prevents them from using a computer, regardless of whether it is easy to use. Tsai et al. (2020) studied technological anxiety and resistance to change in older adults using wearable health technologies. Sayaf et al. (2021) also studied computer anxiety in digital learning at Saudi universities. Similarly, Hu et al. (2022) examined how general anxiety affects college students' intentions to learn online during the COVID-19 pandemic. Therefore, hypothesis H7 is stated as follows:

H7: Anxiety has a negative effect on perceived ease of use.

2.2.8. Perceived Playfulness

Perceived playfulness is the degree of cognitive spontaneity in computer interaction (Webster & Martocchio, 1992). In e-learning, research has indicated that computer playfulness is a crucial external factor in the TAM (Salloum et al., 2019). Algerafi et al. (2023) confirm that perceived playfulness has a positive and significant effect on perceived ease of use. These findings show that students enjoy and perceive AI-based robots as playful and spontaneous. Previous studies have also shown similar results: Hackbarth et al. (2003); Lin et al. (2020). Research has shown that playfulness significantly influences the adoption of hearing aids in modern cities, allowing patients to access services playfully and reducing adoption barriers (Wang et al., 2022). Therefore, hypothesis H8 is stated as follows:

H8: Perceived playfulness has a positive effect on perceived ease of use.

2.2.9. Perceived Enjoyment

Perceived enjoyment is the degree to which the activity of using a specific system is considered enjoyable, apart from any performance consequences caused by using the system (Venkatesh, 2000). Salloum et al. (2019) conducted a literature review with 120 research samples and discovered that perceived enjoyment is one of the most common external factors influencing the acceptance of e-learning. Similarly, regarding the use of chatbots on smartphones for shopping, Kasilingam (2020) emphasized the importance of perceived enjoyment and usefulness. Furthermore, Pillai et al. (2020) studied consumer purchase intentions at AI-powered automated retail stores and identified various predictive factors, including perceived enjoyment. This suggests that perceived enjoyment is vital in determining consumers' willingness to engage with advanced technologies.

Similarly, Camilleri & Camilleri (2019) focused on students' willingness to engage in mobile learning applications and emphasized the motivations of enjoyment for game-based learning. In their research, Algerafi et al. (2023) demonstrated a positive correlation between perceived enjoyment and perceived ease of use. This is reflected in students' enjoyment of the novelty and usefulness of robots as well as their ease of operation and adaptation. Previous studies have also shown similar results, typically similar to two previous studies by scientists, such as Hackbarth et al. (2003) and Lin et al. (2020). Therefore, hypothesis H9 is stated as follows:

H9: Perceived enjoyment has a positive effect on perceived ease of use.

2.2.10. Perceived Ease of Use

Perceived ease of use is the perception that one can easily use technology without investing too much time in in-depth research (Davis, 1989), which means that a person's likelihood of adopting technology is greater if they perceive it as easy to use. Perceived usefulness is a person's subjective belief that a specific technology can improve their career development. People are willing to consider perceived ease of use if they believe it is simple and requires little effort (Roy et al., 2022). Researchers have revealed that perceived usefulness and perceived ease of use are important in predicting technology adoption in education (Cruz-Benito et al., 2019). Previous research has confirmed that perceived ease of use significantly impacts perceived usefulness (Abdullah et al., 2016; Binyamin et al., 2019; Joo et al., 2018; Zogheib et al., 2015). Bailey et al. (2022) reported that perceived usefulness and perceived ease of use positively correlate with student learning through video conferencing technology. Additionally, Antonietti et al. (2022) reported that teachers' beliefs about the usefulness of teaching technology have a positive relationship with their intention to use technology. Aypay et al. (2012) and Lule et al. (2012) reported that perceived ease of use strongly impacts the intention to use AI technology. Hypotheses H10.1 and H10.2 are proposed as follows:

H10.1: Perceived ease of use has a positive effect on perceived usefulness.

H10.2: Perceived ease of use has a positive effect on behavioral intention*.*

2.2.11. Perceived Usefulness

Perceived usefulness can be defined as a person's perception that they will be more productive when using technology (Davis, 1989). When considering AI-based technology, perceived usefulness refers to how students perceive the potential of AI in providing more effective and productive ways of learning (Hien, 2020). According to Davis (1989), the greater the perceived usefulness is, the greater the likelihood of adopting the technology. In Korea, Shin & Lee (2014) determined that the positive effect of perceived usefulness significantly contributed to their intention to use technology in a study of university students' adoption of NFC mobile payments in South China. Chen & Wu (2020) focused on students' intention to use ICT-integrated mathematics remediation tutorials. This has been similarly demonstrated in other domains, such as the adoption of crowdsourcing platforms (Mohd Amir et al., 2020), the use of open-source software (Racero et al., 2020), physicians' intentions to use IoT healthcare devices (Alhasan et al., 2022), and the adoption of e-learning applications by parents of primary school students during the COVID-19 pandemic (Kusumadewi et al., 2021). Moreover, Saari et al. (2022) reported that perceived usefulness significantly influences the behavioral intentions of participants who test new social robots on the market. Perceived usefulness also significantly affects the intention to adopt e-learning (Abdullah et al., 2016; Martinho et al., 2018; Scherer et al., 2019; Wong, 2015). Therefore, hypothesis H11 is stated as follows:

H11: Perceived usefulness has a positive effect on behavioral intention*.*

3. Methodology

Qualitative research has played an important role in refining the scale to suit the use of AI in education for students at the Industrial University of Ho Chi Minh City. In-depth interview methods were used for this purpose. A group of expert individuals, including experts in the field of technology, educators, and AI experts, provided invaluable insights—the sampling procedures adhered to the principle of saturation, with interviews conducted until data saturation was achieved. Adjustments to the scale were then made on the basis of expert judgment.

Furthermore, the questionnaire incorporated items that encouraged a deeper investigation of the survey sample information, as shown in Table 1. Quantitative research was then conducted on the basis of the sample size determined according to Saunders et al. (2009). The formula for determining the sample size is as follows:

$$n \geq \frac{N*Z^2*p*(1-p)}{d^2*(N-1)+Z^2*p*(1-p)} \quad (1)$$

In the above formula, the variable "N" represents the comprehensive measurement scale established on the basis of 36,000 students enrolled at the Industrial University of Ho Chi Minh City in 2024. This specific index solely considers the use of artificial intelligence in the learning process. The symbol "Z" denotes the statistical parameter for the usage level, determined at a 95% confidence interval with a specific value of 1.96. Moreover, the variable "p" represents the anticipated proportion, with an estimated maximum possibility of 50%. The parameter "d" indicates the precision level, with the statistical significance threshold set at 5% in economic studies. The prescribed sample size, denoted by "n," must encompass at least 380 survey responses.

Consequently, the sample size for this research endeavor was determined to be n = 390 > 380. Our subsequent sampling process employs a meticulous stratified sampling method on the basis of the student's year of study. The selection ratio is intricately determined on the basis of the characteristics of students across each year: 10% first-year students, 20% second-year students, 30% third-year students, and 40% fourth-year students. This comprehensive and rigorous approach ensures a robust and representative sample for our research, instilling confidence in the research process.

The survey data will be examined through partial least squares structural equation modeling (PLS-SEM) via SmartPLS 3. Several reasons for choosing SmartPLS 3 over other equation modeling software include the following: (1) to minimize the possibility of data not conforming to a normal distribution; (2) it is suitable for exploratory research; and (3) it facilitates the comparison of findings with previous studies that primarily used SmartPLS 3.

4. Results

4.1. Preliminary assessment of the research sample

After collection, the questionnaires were cleaned and analyzed. Preliminary statistics are shown in Table 1 through criteria such as gender, student year and used time. Among the 390 valid questionnaires after screening, 40% were female, and 60% were male. The groups of subjects with the longest usage time are evenly distributed: the group of subjects with the most usage time is 1 year - < 2 years, accounting for 23.8%, followed by subjects < 6 months, 6 months - < 1 year. Overall, 23.3% and 21%, respectively, of the remaining subjects over 5 years and 3 years (< 5 years), never had the lowest rates, from 4.9%, 4.6% and 13.13%, respectively.

Table 1 Respondents' demographic characteristics.

Criteria		Frequency	Percent (%)
Gender	Male	234	60
	Female	156	40
Student	First year	39	10
	Second year	78	20
	Third year	117	30
	Fourth year	156	40
Used Time	< 6 months	91	23.3
	1 year - < 2 years	93	23.8
	2 years - < 3 years	35	9.0
	3 years - < 5 years	18	4.6
	6 months - < 1 year	82	21.0
	Never	52	13.3
	Over 5 years	19	4.9

4.2. Testing the Measurement Model

The research employs a quantitative method using a structural equation model (SEM) implemented through SmartPLS software. The model assesses the impact of factors related to AI usage for learning among students at the Industrial University of Ho Chi Minh City. It involves 12 specific factors, namely, (1) subjective norms, (2) image, (3) job relevance, (4) output quality, (5) result demand, (6) self-efficacy, (7) anxiety, (8) perceived playfulness, (9) perceived enjoyment, (10) perceived usefulness, (11) perceived ease of use, and (12) behavioral intention. These 12 factors were meticulously evaluated via 46 measurement scales derived from preliminary investigations through qualitative research. The outer loadings of the observed variables examined in this study ranged from 0.644--0.945.

The survey meticulously analyzed the measurement model, employing composite reliability (CR), average variance extracted (AVE), and outer loadings to assess the reliability of the measurements. The findings in Table 2 demonstrate that all relevant indicators for composite reliability, average variance extracted, and outer loadings meet the necessary reliability and overall validity criteria. Additionally, Table 2 presents the Cronbach's alpha values for each construct, all of which exceed 0.7, thus fulfilling the required criteria (Hair et al., 2014).

The study conducted extensive discriminant testing to further evaluate the measurement model by comparing the relationships between variables with average variance extracted (AVE). Discriminant validity was tested against the Fornell–Larcker criterion shown in Table 3, indicating that the square root of the AVE for each construct exceeds the correlation between pairs of concepts. AVE values in the range of 0.7--0.9 are considered statistically significant, confirming the reliability of the measurement model. These values represent a relatively high level of significance when placed side by side with an appropriate level greater than 0.5 (Fornell & Larcker, 1981).

4.3. Structural Model Inspection

The results of testing the structural model are shown in Figure 1. The authors used the adjusted R square index, f square, and path coefficients to evaluate the structural model. On the basis of the linear structural model in Figure 1, the experimental results for INT, PU, IMA, and PEOU are 64.7%, 61.1%, 31.8%, and 28.8%, respectively. The estimation of path coefficients is based on the homeostasis of each dependent variable and the prediction of (Hair et al., 2014). The results from the variance inflation factor (VIF) table show that the associations between predictors do not violate the multicollinearity assumption because all the coefficients are within the acceptable range (VIF = 1.286 – 3.008 < 5), confirming that the model does not violate this phenomenon.

Table 2 Results of reliability and converging values of the scale.

	Cronbach's Alpha	CR*	AVE*
Anxiety (ANX)	0.845	0.896	0.744
Image (IMA)	0.762	0.862	0.676
Behavioral Intention (INT)	0.832	0.881	0.598
Job Relevance (JR)	0.809	0.872	0.633
Output Quality (OPQ)	0.791	0.877	0.705
Perceived Enjoyment (PE)	0.850	0.930	0.869
Perceived Ease of Use (PEOU)	0.780	0.858	0.603
Perceived Playfulness (PF)	0.835	0.901	0.753
Perceived Usefulness (PU)	0.802	0.883	0.716
Result Demonstrability (RD)	0.703	0.817	0.529
Self-Efficacy (SE)	0.831	0.887	0.663
Subjective Norm (SN)	0.820	0.875	0.584

*CR = composite reliability; AVE = average variance extracted.

Table 3 Results of reliability and converging values of the scale.

	ANX	IMA	INT	JR	OPQ	PE	PEOU	PF	PU	RD	SE	SN
ANX	0.863											
IMA	0.324	0.822										
INT	0.100	0.424	0.773									
JR	0.294	0.698	0.540	0.796								
OPQ	0.298	0.595	0.342	0.614	0.839							
PE	-0.000	0.364	0.387	0.462	0.397	0.932						
PEOU	0.141	0.430	0.739	0.567	0.409	0.469	0.776					
PF	0.125	0.404	0.397	0.503	0.513	0.756	0.487	0.868				
PU	0.094	0.424	0.661	0.452	0.466	0.446	0.752	0.543	0.846			
RD	0.110	0.543	0.643	0.593	0.534	0.496	0.574	0.426	0.563	0.728		
SE	0.421	0.541	0.454	0.682	0.638	0.513	0.448	0.583	0.475	0.551	0.814	
SN	0.247	0.566	0.692	0.588	0.541	0.373	0.608	0.427	0.552	0.639	0.510	0.764

By utilizing the Cohen (2013) effect size measure known as the f square effect coefficient, the values of the influence levels of the f square coefficients are presented in Table 4. Each independent variable in the SEM will have a corresponding f square value for its relationship with the dependent variable. The results from the table show that the f-square values of the relationships range from low to high, falling between 0.001 and 0.579. In this table, the most significant effect is observed in the impact of the independent variable PEOU (perceived ease of use) on PU (perceived usefulness), with an f square value of 0.579, as this is the only relationship considered in the univariate regression model. Next is the impact of SN (Subjective Norms) on IMA (Image), with an f square value of 0.471 > 0.35, which is considered a relatively substantial level of impact. Other relationships have a moderate level, such as the impact of PEOU, PU, and SN on INT (Behavioral Intention), where SN still has a more significant impact on INT. The impact of ANX (Anxiety) on IMA and the impact of IMA and SN on PU are considered insignificant, with an f square value < 0.02 (Chin & Marcoulides, 1998). Additionally, the results in Table 4 also show that PE (perceived enjoyment), PF (perceived playfulness), and SE (self-efficacy) have significant impacts on PEOU. Moreover, JR (job relevance), OPQ (output quality), and RD (result demand) also have significant impacts on PU. The model excluded the observed variables ANX2, PEOU2, and PU4 because the variables were not statistically significant when the outer weights and outer loadings were considered (Hair et al., 2017).

4.4.Testing the Research Hypotheses

To further emphasize the reliability of the study, the author continued to use Bootstrapping analysis techniques (n = 5000) to test the research hypotheses. The results are presented in detail in Table 5. From these results, we can decide which hypothesis is supported when concluding that there is a significant impact in the structural model through the T-statistic or P-value. The results show that all hypotheses about the impact relationship in the linear structural model are accepted, shown through the T-statistic results, all of which are greater than 1.96. However, hypotheses H1.2, H2, and H7 are rejected because the impact is within the 95% statistical significance range.

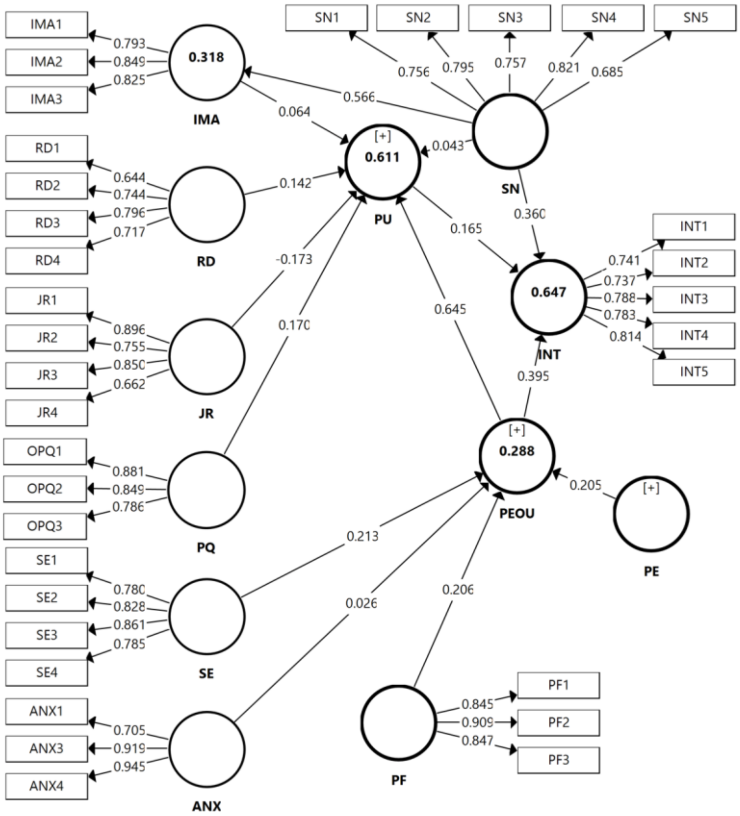

Figure 1 Results of the linear structural model inspection.

Table 4 Index result of f square.

	ANX	IMA	JR	OPQ	PE	PEOU	PF	PU	RD	SE	SN
IMA											0.471
INT						0.171		0.032			0.227
PEOU	0.001				0.024		0.022			0.033	
PU		0.005	0.030	0.040		0.579			0.025		0.002

Table 5 Hypothetical test results.

Hypothesis	Relationship	Coefficient	P Values	Result
H1.1	SN ➔ IMA	0.566	0.000	Accept
H1.2	SN ➔ PU	0.043	0.479	Rejected
H1.3	SN ➔ INT	0.360	0.000	Accept
H2	IMA ➔ PU	0.064	0.218	Rejected
H3	JR ➔ PU	-0.173	0.005	Accept
H4	OPQ ➔ PU	0.170	0.002	Accept
H5	RD ➔ PU	0.142	0.009	Accept
H6	SE ➔ PEOU	0.213	0.009	Accept
H7	ANX➔PEOU	0.026	0.676	Rejected
H8	PF ➔ PEOU	0.206	0.021	Accept
H9	PE ➔ PEOU	0.205	0.023	Accept
H10.1	PEOU ➔ PU	0.645	0.000	Accept
H10.2	PEOU ➔ INT	0.395	0.000	Accept
H11	PU ➔ INT	0.165	0.002	Accept

5. Discussion

Hypotheses H1.1, H1.2, and H1.3 tested the impact of the subjective norm (SN) on three variables: image (IMA), perceived usefulness (PU), and behavioral intention (INT). The results in Table 5 show that the P values of the impact of SN on IMA and INT are both 0.000, so these two impacts are statistically significant. The standardized impact coefficients of SN on IMA and INT are 0.566 and 0.360, respectively, indicating that subjective norms significantly positively affect image and behavioral intention. Therefore, hypotheses H1.1 and H1.3 are accepted. This conclusion is entirely consistent with the study of Algerafi et al. (2023). The overall impact of SN on PU is not statistically significant at the 5% level (P value = 0.479). Therefore, hypothesis H1.2 is rejected, similar to the study of Saari et al. (2022) but inconsistent with the study of Algerafi et al. (2023). The impact relationship of IMA on PU was also rejected when this impact did not reach the allowed statistical significance, as mentioned, which shows a significant difference from the studies of Setiyani (2021) and Algerafi et al. (2023). This new difference will be discussed further in the following content. In hypothesis H7, considering the relationship between ANX and PEOU also gives a similar relationship, subsequent studies can consider the direct impact of ANX on INT instead of through PEOU because this relationship has been rejected. This conclusion is similar to the study of Algerafi et al. (2023) but different from Saari et al. (2022). In the study of Saari et al. (2022), ANX showed a significant negative correlation with PEOU. The remaining hypotheses all show significant similarities with recent studies, and in the next section, we will discuss the more profound relationships.

Perceived ease of use (PEOU) is a crucial foundation for perceived usefulness (PU). Students will perceive AI as useful in learning if it is easy to use and access. Subjective norms (SNs) stand out as a significant factor influencing students' image (IMA) when learning with the support of AI tools. When individuals within a university use AI, they tend to have more prestige than those who do not (IMA1), enhance their CVs (IMA2), and improve their image in the eyes of recruiters (IMA3). As a result, students are more inclined to use AI technology throughout their studies at the university.

The research findings indicate that perceived usefulness (PU), perceived ease of use (PEOU), and subjective norms (SNs) significantly impact students' intention to use AI in learning (INT). Many students have a positive attitude toward applying technology to their studies. They believe that AI tools offer various forms of access (PEOU1), are easy to use for learning (PEOU3), make learning more engaging (PEOU4), and are versatile (PEOU5). Moreover, using AI for learning purposes directly impacts performance (PU1), effectiveness in understanding concepts (PU2), and acquisition of new knowledge (PU3). Furthermore, the influence of external factors also motivates students to use technology for their education, such as influencers (SN1), essential people (SN2), lecturers (SN3), platforms (SN4), and people around them (SN5).

The findings reveal that students' self-efficacy (SE), perceived enjoyment (PE), and perceived playfulness (PF) are essential factors influencing their perceived ease of use (PEOU) of AI in their studies. Students will always feel comfortable adopting new technology if they find it enjoyable, which contributes to the effectiveness of their learning.

Output quality (OPQ), result demand (RD), and job relevance (JR) are crucial factors affecting the perceived usefulness (PU) of AI in education. This suggests that AI is accepted among students because when they apply technology to their studies, the output quality (OPQ1), standards (OPQ2), and learning outcomes (OPQ3) clearly and positively improve, even exceeding expectations. In addition, with the continuous development of technology today, students do not hesitate to emphasize the importance of applying the convenience of this era, which is AI. Research indicates that in the university setting, using AI for support is very important (JR1), and learning is more difficult without AI (JR2). The results also confirm that students' current level (JR3) and the subjects at the university (JR4) are entirely suitable and feasible for the application of AI. Finally, students feel confident and confident in disclosing their use of AI to support their learning (RD1). They are willing to communicate negative downsides (RD2), positive outcomes (RD3), and evidence (RD4) after learning with the help of AI. Therefore, anxiety (ANX), image (IMA), or subjective norms do not affect students' use of AI in learning.

6. Conclusions

This study assesses students’ intention to use AI technology in their learning at Ho Chi Minh City University of Industry. In previous studies, the authors often ignored the TAM3 model and focused mainly on evaluating models such as the TAM, TAM2 and UTUAT. In this study, the team used the TAM3 model to propose hypotheses to clarify students’ feelings about the decision to use AI in their learning. From the above discussion, some policy implications for many subjects with different perspectives can be suggested.

In future research, this study could serve as a reference for subsequent investigations into measuring students' attitudes toward AI tools and their adoption in learning. However, this research has several limitations. First, the short research duration limited the depth of the study. Second, this research only collected data from undergraduate students; these data could be expanded to include postgraduate students or distance learning students for more novel findings. Simultaneously, the study was conducted with students at the Industrial University of Ho Chi Minh City, so the results only represent this institution.

Additionally, the respondents' answers could have been more objective, possibly leading to data inaccuracies. Therefore, other methods and data collection approaches should be considered to increase the accuracy of the research. Furthermore, in addition to the factors mentioned in this topic, many external factors and elements still need to be addressed in this study. Finally, the contributions and suggestions of the group are subjective and based on the research. Therefore, each university may have a different approach. Our research team believes that the limitations of this study serve as a foundation for building and improving future research endeavors.

Acknowledgment

We sincerely thank the reviewers for their valuable feedback and suggestions, which have contributed significantly to improving this manuscript. We would also like to thank the experts and those who participated in this scholarly survey.

Ethical considerations

Our research was conducted with a strong commitment to ethical standards. All interviews were carried out with the informed consent of the participants, ensuring their voluntary participation and the confidentiality of their responses.

Conflict of interest

The authors declare no conflicts of interest.

Funding

This study was funded under the internal expenditure regulations of INDUSTRIAL UNIVERSITY OF HCM CITY (Decision No. 568/QD-DHCN).

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