The Relationship between Students' Perceptions of AI Applications and Intention to Use, Mediating Role of Satisfaction

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Abstract. This study explores the relationship between how students perceive AI applications and their willingness to use these technologies in higher education. The study is based on the educational environment of Vietnam, where there is a simultaneous occurrence of rapid technical progress and educational development. The researchers utilized quantitative surveys in this study, gathering data from a broad sample of students enrolled in higher education institutions. The study utilized structural equation modeling (SEM) to examine the intricate connections between students' perceptions of AI applications, their contentment with these technologies, and their inclination to adopt AI-driven tools for educational purposes. The findings emphasize the crucial function of satisfaction in mediating the relationship between perceptions of AI applications and plans to adopt them. Additionally, perceived ease of use, perceived usefulness, personal learning profile, personal learning environment specific to the Vietnamese context are explored in depth, clarifying on the ways in which these factors shape students' attitude and behavior towards AI in higher education.

Keywords: AI Applications, Higher Education, Intention to Use, Satisfaction, Students' Perceptions, Vietnam.

1. Introduction

Artificial intelligence (AI) and sustainable development have become two important topics that are widely discussed. However, it is only in recent years that the role and implication of AI on sustainable development has received increasing attention. It has a substantial effect on a variety of disciplines, including medical, finance, industry, law, and entertainment. Education is no exception, and there is a considerable amount of research now underway into AI applications for education, such as intelligent tutoring systems, adaptive learning teaching, assessment design, and learning analytics (Salas-Pilco & Yang, 2020). As the study of AI in education is continually

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growing and changing, there is a requirement to enhance academic comprehension of AI in education. AI-based applications for higher education are becoming increasingly prevalent around the world, including in Viet Nam, where AI research is being conducted and some AI applications are being implemented to upgrade university services, support teachers in providing quality education, and encourage the learning of students.

Furthermore, the idea of AI compounded with Mobile teaching and learning (M-learning) is emerging in higher education (Pedro et al., 2018), which can afford new opportunities to enhance pedagogical flexibility, learning process or outcome, and feedback immediacy (Cheung, 2015). For instance, Vio-Edu using AI to detect students' strengths and knowledge gaps, the system will synthesize and analyses data regarding students' learning behaviors and abilities. This will also allow the system to suggest study plans that are appropriate for each student. In terms of Chatbots, a Chatbot is an artificial intelligence (AI) based software program that is able to simulate a conversation with the user using natural language through messaging platforms, phone applications and websites. Chatbots with education intentionality are used in fostering teaching and learning. For instance, the ChatGPT chatbot uses artificial intelligence to provide the most gratifying answers to all user questions. ChatGPT can simulate discourse, respond to inquiries in context, acknowledge errors, refute false premises, and reject inappropriate requests thanks to this learning technique.

However, several aspects of natural language processing in AI applications may confuse students, making it difficult for them to grasp or interpret its response. For that reason, certain interactions between people and AI applications are challenging as the AI language does not completely comprehend natural language. Additionally, there is little research focused on user perception of AI in higher education. Thus, this research suggests the urgency for conducting a synthesis and evaluation of AI-related research findings in order to emphasize the advances that have been brought to higher education by AI to promote quality teaching and learning. Therefore, in this study, we will investigate students' perceptions of AI applications and intention to use in higher education.

This study attempts to achieve the following objectives:

- Identify the perception of the students concerning the role of artificial intelligence (AI) in E-learning.
- Identify the important factors affecting students' intention to use AI applications in higher education.
- Find out the relationship between students' perceptions of AI applications and behavioral intent to use them effectively in higher education.

To contribute to a better understanding of the role of AI applications in E-learning, this research seeks to answer the following three research questions:

RQ1. Do AI applications affect the perceived ease of use, perceived effectiveness and perceived usefulness of the students' E-learning?

RQ2. Does satisfaction mediate the relationship between students' perceptions of AI applications and intention to use in higher education?

RQ3. What factors decide the students' overall intention to use AI applications for E-learning?

The remainder of this research is structured as follows: second section presents a literature review of the article, including the theoretical background and hypothesis development. Next is materials and methods, followed by the results of this study. Finally, there is our discussions and conclusions, which includes theoretical contribution, practical implication, limitations, and future research.

2. Literature Review

2.1 AI Applications

AI application refers to the utilization of artificial intelligence techniques, algorithms, and technologies to perform specific tasks or solve problems across various domains. AI Applications can be used to analyze students' learning process, including interaction content, learning behaviors, test results and learning perceptions, to provide instant support or feedback to individual students as well as suggestions to teachers for improving teaching content and strategies. Scholars have indicated that facilitating personalized learning is among the key objectives of Artificial Intelligence in Education. Presently, there are also relevant literature reviews in the AIEL field, but some of these literature reviews only focus on a certain discipline (e.g., mathematics, Huang, Teo, & Scherer, 2022) or a specific field (Chan-Olmsted, 2019).

In this study, the authors focus on two key factors of AI Application in E-learning: Chatbot and Mobile teaching and learning (M-learning). A chatbot is an artificial intelligence automated software tool that simulates a conversational interaction between the user and a computer, using natural language. Where chatbot technology is enabled, the end user is able to 'talk' to a pre- built AI chatting robot, rather than a human individual. Since the emergence of Eliza, chatbots based on artificial intelligence generated content technology have been continuously developing and innovating (George and Lal, 2019). The emergence of chatbots such as Microsoft Xiaoice and Google Siri, as well as the continuous upgrading of technologies such as Chat GPT, marks the entry of this development process into a spiral upward historical stage). The second type of AI tool consists of personalized learning websites, apps, and programs such as Duolingo, ELSA Speak, and Vio-Edu. These tools using AI help users become more proficient by personalizing instruction to each user's knowledge level.

2.2 AI in Higher-Education

AI dominates the fields of science, engineering, and technology, but also is present in education through machine-learning systems and algorithm productions. The field of AI in education has demonstrated technological advances, theoretical innovations, and successful pedagogical impact (Roll & Wylie, 2016), with diverse applications such as intelligent tutors for content delivery, feedback provision, and progress supervision (Bayne, 2015). Moreover, AI in education is primarily recognized through various algorithmic applications and advanced computer programs, such as language correction (Grammarly and Google Docs) to find out and correct errors in written text inputs, or recommend corrections that the person sending them can choose to accept or decline; personalized learning (Vio-Edu) to assist students in becoming more proficient by personalizing instruction to the student's understanding level; learning analytics (Learning Management Systems) to predict a student's course achievement based on interaction data; and many others different applications computer programs, such as recommender chatbots (ChatGPT), personal assistants (Apple's Siri and Google Assistant), and learning apps (Duolingo and ELSA Speak)

(Mohammadi, 2015). AI in education may be used to offer specific assistance and enhance awareness of knowledge gaps, enabling students to learn more effectively and efficiently through personalized and adaptive instruction.

2.3 Students' Perception

It is necessary to do research on students' perceptions in order to determine their intention to use AI applications in higher education. Perception is someone's thoughts about something that they learn to measure how their attitude toward using something, whether they agree or not about the method or about something that they learn (Hong, 2003). To produce an achievement, the process also occurs in students' views of learning in class. Students' perceptions, according to (Shidu, 2003), "are students' point of view toward something that happened in learning process class and produced it with suggestions or arguments for teacher or classmate to improve their learning process". We can take examples of how students perceive AI applications in E-learning. AI applications used in E-learning are particularly significant to certain students because they believe that using these apps will improve their academic achievement. However, for most other students, employing AI applications in E-learning is a waste of time; they are uninterested in it. We can observe from that example that students' perceptions are diverse. Not everyone believes in and intends to deploy AI applications in E-learning.

2.4 Theoretical Framework

The Technology Acceptance Model (TAM) model has two major constructs: perceived usefulness and perceived ease of use (Davis, 1989). According to Davis (1989), when users of an information technology-based system think that the IT platform is beneficial and easy to use, it leads to a positive attitude, which causes the users to continue using the system. TAM is based on Davis's Theory of Reasoned Action (TRA) in creating links between components to explain human actions to accept and use an object. TAM may be extended by adding external variables in addition to fundamental components. In particular, TAM has been widely applied within the domain of E-learning (Šumak et al., 2011). Later, research extended the TAM by adding various factors to account for the influences of other environmental and motivational characteristics (Li et al., 2021; Salimon et al., 2021). These additional factors strengthen the original model for greater predictive power and adapt the TAM to a range of E-learning contexts.

Recent years have seen the emergence of research examining factors that influence students' implementation of intelligent tutoring systems using the extended TAM. This theory is widely recognized and has been widely applied in the field of applied technology research. TAM (Davis, 1989) focuses on the cognitive and social factors that shape individuals' acceptance and use of technology to explain the determinants of technology adoption and use. By using these theories as a theoretical framework, this study aims to determine student's perception on AI applications as well as satisfaction when using these AI applications. The use of this theory will allow for a more comprehensive understanding of the fundamental factors that shape students' intention to use AI applications in Vietnam.

In order to explain the technology acceptance of the users in more detail, TAM can be expanded by adding external variables besides basic structures and this is an extended TAM approach (Hong & Yu, 2018). Therefore, in this research, we use TAM as a theoretical basis which has two available variables as perceived of usefulness and perceived ease of use; and four external variables as perceived of effectiveness, personal learning profile, personal learning environment and satisfaction. These factors can be directly utilized to investigate the intention to use AI applications in higher education.

2.5 Hypotheses Development

Perceived ease of use represents an intrinsically motivating component of the student-technology interaction. Students are free to choose various kinds of digital technologies to access many kinds of information. Moreover, when such a platform, allows the learners to submit their given assignments anywhere, and check for plagiarism, the system would be considered easily used and adopted because the users perceive that their expectations have been met (Hwang et al., 2014). AI applications such as Chatbots for e-service offer an entirely new way to satisfy users (Conde et al., 2020) because such programs "serve a range of roles, from personal assistant, to intelligent virtual agent, to companion" (Rahaman et al., 2023, p. 4).

Prior studies have also confirmed the positive relation between perceived ease of use and favorable attitude or satisfaction (Chang & Wang, 2008), among individual's ease of use, perceive usefulness and intentions in the context of E-learning (Pituch & Lee, 2006). Specifically, student is more likely to develop satisfaction and have favorable intentions toward online experiences if it is perceived to be useful (Bhattacherjee, 2001). Therefore, we expect positive correlation between perceived ease of use and learning satisfaction. Accordingly, the following hypothesis is formulated:

H1: Perceived ease of use is related to students' satisfaction with AI applications.

The advancement of artificial intelligence can make academic students' programming more enjoyable and satisfying. Students can obtain a more appropriate teaching plan and can automatically summarize and analyze previous learning and fill in gaps in knowledge at regular intervals, so that they can know their learning situation at any time and can review and practice according to tips, thereby greatly improving learning efficiency. The ultimate purpose of learning is to gain knowledge. Student perceptions of the overall usability of the course are likely associated with student satisfaction and learning outcomes (Evans & Abbott, 1998). Learning satisfaction according to Khayati & Zouaoui (2013), relates directly to perceptions and feelings about learning effectiveness or outcomes.

Learners can conduct more tailored, immersive, and entertaining learning in a virtual fusion environment with the support of artificial intelligence. When the learner completes the learning assignment, AI praises them and supervises and encourages them when they do not, so that the learner feels humane care and actively completes the learning task without the pressure and demand of teachers and parents (Evans & Abbott, 1998). AI can have a great impact to help students increase productivity, enhance performance, improve learning effectiveness and as a result achieve student's satisfaction. Accordingly, the following hypothesis is proposed:

H2: Perceived effectiveness is related to students' satisfaction with AI applications.

Many studies have shown that perceived usefulness is a factor of user pleasure (Hadji & Degoulet, 2016). Meanwhile, (Amin et al., 2014) proposed that perceived ease of use, in addition to perceived usefulness, is a predictor of satisfaction. As a result, there is a considerable influence of perceived usefulness on satisfaction with the help of AI applications for students in higher education when compared to the remote learning system or E-learning system. Through the use of machine learning, these are programmed to learn from their previous conversations. This learning process often takes place under active development supervision. For example: Chatbots in learning apps (Duolingo and ChatGPT) are typically employed in dialog systems where information is shared. Bradford & Laurence (2017) feel that chatbots could be useful as instructional assistants in roles that do not require them to answer sophisticated practical problems. The students seemed to be interested in the questions that were answered by the algorithm which helped them to improve their performance in higher education and bring about desired satisfaction (Daneji et al., 2019). Therefore, some investigations have found a strong and beneficial influence of perceived usefulness on satisfaction in E-learning that using chatbots. The following hypothesis is formed:

H3: Perceived usefulness is related to students' satisfaction with AI applications.

In this study, we assume satisfaction can be defined as the degree to which one believes that an experience evokes positive feelings which have positive effects on future intention. Previous research indicates that feelings of satisfaction have a significant influence on continuation intention. For instance, satisfaction was a vital antecedent of continuance intention of electronic commerce service (Bhattacherjee, 2001), web-based learning (Crompton & Burke, 2023), and online tax-filing (Clark & Mayer, 2016). Thus, we conclude from previous findings to infer that an individual who generally feels more satisfied with their usage experience would intend to use these E-learning systems more frequently in the future. Therefore, in the context of this study, satisfaction is assumed to have a positive impact on intention to use AI applications in E-learning. Accordingly, the following hypothesis is formulated:

H4: Satisfaction is related to students' intention to use AI applications.

Montebello (2018) said that personal learning profiles can be advantageously employed within an online environment as access to the right resources to match the same portfolio is more comfortable and efficient. Besides, as mentioned above, perceived ease of use is a student's assessment of their interaction with the Internet-based learning systems (ILS). So it makes it convenient and easy for students to use a personal learning profile, resulting in them feeling the ease of use in AI applications. Therefore, we expect that personal learning profile can influence learners' perceived ease of use with AI applications.

Gooren-Sieber et al. (2012) suggested that a learning portfolio is usually defined as a student's academic record that accurately captures the work performed and the achievements attained over the years. Besides, Daunert & Price (2014) suggest that personal learning profile is practical tools that encourage self-directed learning that reflect the learners' specific academic achievements. Therefore, it helps to recognize and achieve learners' learning results. So that applying personal learning profile in AI applications will improve learning efficiency. This helps learners to improve themselves, develop and correct their weaknesses. Hence, we concluded that personal learning profile can influence learners' perceived effectiveness.

Some researchers (Attwell, 2007; D'Alessandro, 2011) attribute the use of portfolios to a rise in enthusiasm as learner's initiate and participate in new learning processes, especially within their network. As a result, personal learning profile will help learners improve their performance by using a particular system. So we concluded that a personal learning profile will influence learners' perceived usefulness. Hence, the following hypotheses are formulated:

H5a: Personal learning profile is related to the perceived ease of use with AI applications.

H5b: Personal learning profile is related to the perceived effectiveness with AI applications.

H5c: Personal learning profile is related to the perceived usefulness with AI applications.

When AI applications can be easily integrated into existing personal learning environment tools, such as learning management systems or productivity software, learners may perceive them as more user-friendly. Besides, the ability to access and use AI applications within familiar personal learning environments reduces the learning curve and enhances the overall user experience (Laurence, 2017). A well-designed interface, clear navigation, and intuitive features can enhance learners' comfort and confidence in using AI applications. Moreover, learners can adapt the AI application's settings, features, or recommendations to align with their learning style and goals, they may find it more intuitive and easier to use. So it makes it convenient and easy for students to use a personal learning environment, resulting in them feeling the ease of using AI applications in education.

Learners can integrate AI applications and resources into their personal learning environment. AI applications (virtual assistants, chatbots, or intelligent tutoring systems) can provide immediate assistance and analyze learners' preferences, performance to deliver customized content, recommendations, feedback (Daunert & Price, 2014). Through these features, learners could leverage the capabilities of AI to achieve their learning outcomes. So, learners perceive the integration of AI applications within their personal learning environment as effective since they receive tailored learning experiences that meet their individual needs and preferences. Hence, we concluded that applying AI applications in personal learning environment can influence learners' perceived effectiveness.

The availability of data-driven insights within the personal learning environment enhances learners' perceived usefulness by empowering them to make informed decisions; optimizing their learning strategies and ensuring their access to valuable and relevant materials (Chung et al., 2018). Therefore, AI applications within the personal learning environment can assist learners in discovering relevant and high-quality learning resources, advanced learning tools and resources. So the personal learning environment will help learners improve their performance by using a particular system. Hence, the following hypotheses are formulated:

H6a: Personal learning environment is related to the perceived ease of use with AI applications.

H6b: Personal learning environment is related to the perceived effectiveness with AI applications.

H6c: Personal learning environment is related to the perceived usefulness with AI applications.

We suggested an enhanced TAM model based on the existing research to give more relevant information to understand the drivers influencing students' desire to use of AI applications in E-learning for higher education in the Vietnam context. When applied to various topics and circumstances, the initial TAM is somewhat deficient (Wang et al., 2022). As a result, an expanded TAM is required for the current study on AI applications for higher education.

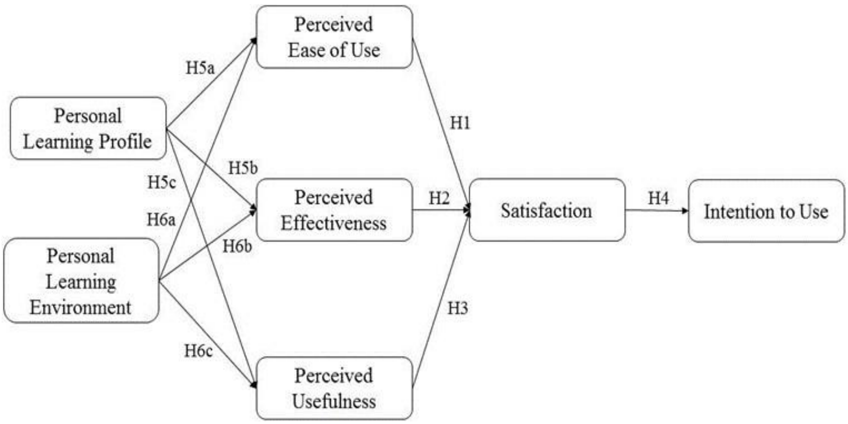

Fig. 1. Proposed Research Model (Source: Authors' proposal)

3. Methodology and Data

A practical non-probability sampling technique was used in the research. The non-probability sampling method is employed because it saves a lot of time and money, according to Cooper and Schindler (1998). The responders included the group with a university degree, the group with postgraduate degree holders and those with college diplomas. Most of the sample above 80% was the group with a university degree. According to the sample characteristics, our study is biased toward students, who have positive intentions towards AI applications. Moderators of the survey indicate that this profile of all users corresponds to their understanding of AI applications in E-learning. As a result, non-response bias was unlikely to be a problem.

This study designed an online survey and collected 450 responses from internet users. Data collection took place from September 2023 to December 2023. To ensure that the responses collected were congruent with our research objectives, we employed certain screening criteria to recruit relevant respondents. The questionnaire was used as a survey instrument to target respondents with people who have education level in university mainly. We explained to the participants before data collection that the study was purely academic and that their identities would not be made public in any reports. Additionally, we told them that there were no right or wrong responses and urged them to be open-minded and truthful in their responses. The survey questionnaire was created on Google Forms. We had 420 responses left after eliminating 30 incomplete answers, and these were used for further research.

This study employs quantitative data analysis methods. It covers how participants are identified, the sources of documents and electronic data, as well as pre-prepared questionnaires and interview questions. Our study has two main methods to analyze data. Firstly, we check the scale by analyzing the reliability co-efficient Cronbach's Alpha. Secondly, the Structural Equation Modeling (SEM) method with SmartPLS 4.0 software tool is used to verify the research model to verify the measurement model, the correlation, and the regression determination.

In addition, the authors conducted an extensive literature review to identify existing measures for topics related to AI applications, student's perception, intention to use and higher education. Personal Learning Profile (PLP) is the first notation that includes six items (Kashive, Powale, & Kashive, 2020). Perceived Ease of Use (PEU) and Perceived Usefulness (PU) were adapted from the study of Malik, Shrama, Trivedi, & Mishra (2021). Next, Perceived Effectiveness (PE) underlying six items were operationalized from previous research of Liaw (2008). Finally, Satisfaction (SA) and Intention to Use (IU) were adapted from Arbaugh (2000) and Ashfaq, Yun, Yu, & Loureiro (2020).

4. Results and Discussions

This section investigates and estimates the data used in this study. Firstly, the authors will describe the sample characteristics and descriptive statistics. Secondly, the author conducted a factor analysis and reliability test in SmartPLS 4.0 to examine the variable consistency. The next step illustrates the empirical results of the proposed hypotheses. The data in this study are taken in 2023; the total time for collecting the data from respondents will be approximately four months. In sum, 450 responses were received. After screening to fulfill the conditions mentioned above, 420 responses were retained and consumed for further data analyses. The detail of the sample characteristics will be shown in the following sections.

Table 1. Sample characteristics

Characteristics	**Frequency (N = 420)**	**Percent (100%)**
Gender		
Male	188	45
Female	232	55

Educational qualifications		
College	68	16
University	306	73
Post-graduate	46	11
Major		
Business	176	42
Social science	83	19
Engineering	125	30
Health	36	9

Gender: The results of the descriptive statistics show that the percentage of males participating in the survey is 45% (188 responses), which is lower than the percentage of females, accounting for 55% (232 responses).

Educational qualifications: The results indicate that the group with a university degree accounts for the highest proportion, at 73% (306 individuals), followed by college diplomas with 68 responses (16%), and the lowest proportion is post-graduate students, with 46 responses participating in the survey (11%).

Major: The results reveal that the business sector has the largest representation among the surveyed subjects, with 176 responses (42%). Next, the engineering sector comprises 125 responses (30%). The third group is social science, with 83 responses (19%). Finally, the health sector with 36 responses (9%).

Composite Reliability (CR): The authors test the reliability through the CR (Composite Reliability) index which is preferred by many researchers over Cronbach's Alpha because Cronbach's Alpha. If the scale is multidimensional (measuring multiple distinct constructs), Cronbach's Alpha may not provide accurate estimates of reliability. Composite Reliability is better suited for assessing the reliability of multidimensional scales. According to confirmed studies, the CR index should be at the threshold of 0.7 (Henseler & Sarstedt, 2013).

Average Variance Extracted (AVE): The Average Variance Extracted is calculated for each unidirectional factor, which will be run separately for each one. To have the appropriate AVE, it needs to be greater than or equal to 0.5 (Fornell & Larcker, 1981).

Outer Loading: The Outer Loading coefficient estimates the relationships between specific observable variables and latent variables. It is calculated as the square root of the absolute value of R^2 of linear regression from latent variable to the observed subordinate variable. All outer loadings of all items should be statistically significant and should be at least 0.708 (Hair et al., 2014). If the outer loadings are less than 0.708, then this study examines the effect of removing the item on composite reliability. Hair et al (2014) also suggested that researchers remove the items having outer loadings between 0.40 and 0.70 if deleting the items leads to an increase in composite reliability and average variance extracted (AVE). Researchers must eliminate the items from the construct if the items have outer loadings of less than 0.40 (Hair et al., 2014).

Table 2. Construct Reliability and Validity

Items	Outer loadings	CR	AVE
PLP1	0.835	0.885	0.719
PLP2	0.849		
PLP3	0.861		
PLE1	0.919	0.898	0.815
PLE2	0.887		
PEU1	0.788	0.849	0.585
PEU2	0.671		
PEU3	0.792		
PEU4	0.801		
PE1	0.751	0.858	0.669
PE2	0.832		
PE3	0.866		
PU1	0.864	0.879	0.708
PU2	0.811		
PU3	0.848		
SA1	0.840	0.934	0.701
SA2	0.836		
SA3	0.846		
SA4	0.836		
SA5	0.852		

Items	Outer loadings	CR	AVE
SA6	0.815		
IU1	0.864	0.910	0.772
IU2	0.890		
IU3	0.882		

In Table 2, loadings of all indicators of the constructs were above 0.7. Also, Cronbach's Alpha were more significant than 0.7 (DeVellis & Thorpe, 2021).

The Fornell-Larcker criterion and Heterotrait-Monotrait ratio (HTMT) were used (Henseler, Ringle & Sarstedt, 2015). The following sections showed that the square root of the AVE (the diagonal elements) of each construct was more significant than other inter-construct correlations, providing evidence for satisfactory discriminant validities of the constructs. The results of HTMT also showed that discriminant validity was not an issue for this study when all Heterotrait-Monotrait ratios of the correlations between the constructs were smaller than the threshold of 0.85 (Hair et al., 2014). As a result, it consolidates the discriminant validity of studied constructs.

Table 3. Correlations between Research Constructs (Fornell-Larcker Criterion)

	IU	**PE**	**PEU**	**PLE**	**PLP**	**PU**	**SA**
IU	1.000						
PE	0.667	1.000					
PEU	0.594	0.682	1.000				
PLE	0.593	0.565	0.663	1.000			
PLP	0.675	0.616	0.664	0.695	1.000		
PU	0.692	0.744	0.699	0.581	0.660	1.000	
SA	0.789	0.690	0.721	0.730	0.744	0.718	1.000

Following Fornell and Larcker (1981) criterion, the author compared the square root of the AVE value of each construct with the highest bivariate correlations with other constructs. The results indicated that the square root of each AVE was greater than its highest bivariate correlations and thus demonstrated that the discriminant validity was acceptable (Table 3).

In addition, the authors will evaluate the model fit by using Chi-squared, SRMR and NFI index. SRMR (Standardized root mean square residual) is the difference between the actual data and the proposed model. The index ranges from 0 to 1 (the smaller the better), especially the ideal index is less than or equal to 0.05. If the SRMR equal to 0, the proposed model completely matches the data. According to Gurtner & Soyez (2016), if the model has an SRMR value less than 0.1, the model is considered to be in agreement with the actual data. The NFI (Normed Fit Index) needs to be greater than 0.5 in order that the model is suitable for the survey context.

Table 4. Results of the model fit test

Notation	Result
SRMR	0.057
Chi-Square	954,939
NFI	0.791

The results show that the model has a Chi-square index equal to 954,939. SRMR = 0,057 < 0.1 and NFI = 0,791 > 0.5 show that this model is suitable for this research (Table 5).

Table 5. Regression test result

	β	Standard Deviation (STD)	T Statistics	P Values
Personal learning environment (PLE) →Perceived Ease Of Use (PEU)	0.389	0.059	6.610	0.000
Personal learning environment (PLE) →Perceived Effectiveness (PE)	0.395	0.059	6.686	0.000
Personal learning environment (PLE) →Perceived Usefulness (PU)	-0.041	0.137	0.303	0.762
Personal learning profile (PLP) → Perceived Ease Of Use (PEU)	0.137	0.106	1.296	0.195
Personal learning profile (PLP) → Perceived Effectiveness (PE)	0.235	0.074	3.154	0.002
Personal learning profile (PLP) → Perceived Usefulness (PU)	0.497	0.071	7.036	0.000
Perceived Ease Of Use (PEU) → Satisfaction (SA)	0.429	0.066	6.491	0.000
Perceived Effectiveness (PE) → Satisfaction (SA)	-0.034	0.038	0.892	0.372
Perceived Usefulness (PU) → Satisfaction (SA)	0.419	0.078	5.410	0.000

	β	Standard Deviation (STD)	T Statistics	P Values
Satisfaction (SA) →Intention (IU)	0.789	0.031	25.357	0.000

The regression model is described as follows:

PEU = 0,389PLE + 0,395PLP PE = -0,041PLE + 0,137PLP PU = 0,235PLE + 0,497PLP SA = 0,419PU - 0,034PE + 0,429PEU IU = 0,789SA

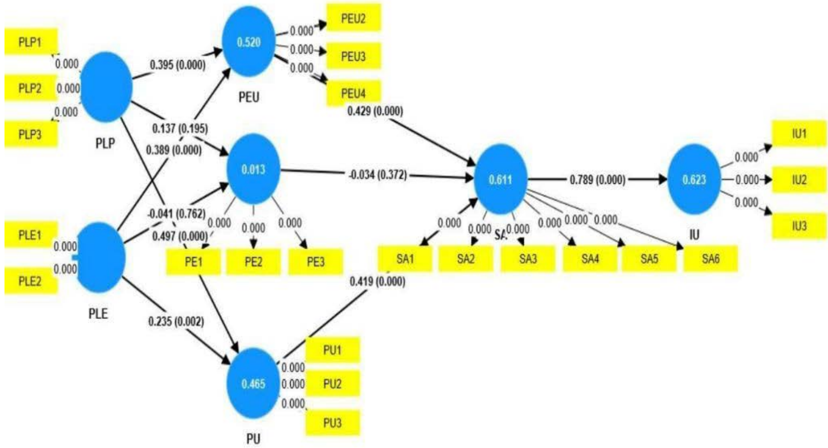

Fig. 2. SEM Model (Source: Authors' calculation)

This section summarizes the hypotheses testing results in this study. Out of ten hypotheses, seven are supported, and collected data do not support three hypotheses (Table 6).

Table 6. Summary of hypothesis testing results

Hypotheses	β	P-values	Hypotheses Testing
H1: Perceived ease of use is positively related to students' satisfaction with AI applications.	0.429	0.000	Accepted
H2: Perceived effectiveness is positively related to students' satisfaction with AI applications.	- 0.034	0.372	Not Accepted
H3: Perceived usefulness is positively related to students' satisfaction with AI applications.	0.419	0.000	Accepted

H4: Satisfaction is positively related to students’ intention to use AI applications.	0.789	0.000	Accepted
H5a: Personal learning profile is positively related to the perceived ease of use with AI applications.	0.395	0.000	Accepted
H5b: Personal learning profile is positively related to the perceived effectiveness with AI applications.	0.137	0.195	Not Accepted
H5c: Personal learning profile is positively related to the perceived usefulness with AI applications.	0.497	0.000	Accepted
H6a: Personal learning environment is positively related to the perceived ease of use with AI applications.	0.389	0.000	Accepted
H6b: Personal learning environment is positively related to the perceived effectiveness with AI applications.	-0.041	0.762	Not Accepted
H6c: Personal learning environment is positively related to the perceived usefulness with AI applications.	0.235	0.002	Accepted

For perceived ease of use, after collecting data and checking it, the results show that it has a positive impact on students’ satisfaction with AI applications **β = 0.429**. This means that **H1** is approved as expected. When approaching novel study tools, students usually concern more about the convenience and accessibility of tools. In particular, the perceived ease of use factor brings the feeling of motivation for students when using AI applications in E-learning. This result supports the similar result with previous research conducted by Amin, Rezaei, & Abolghasemi (2014) which states that mobile learning should be easy to use and easy to learn in order to attract users.

On the other hand, **H2** —perceived effectiveness has no significant impact on students’ satisfaction (**β = -0.034**). AI applications in E-learning might introduce complexity that users struggle to grasp initially. This could lead to a situation where users do not fully understand the benefits or the ways in which AI is enhancing their learning experience, thus impacting their perception of effectiveness and subsequently satisfaction (Almarashdeh, 2016). Moreover, users might not be familiar with AI concepts and how they apply to E-learning. Even if something is perceived as effective, it might not certainly contribute significantly to satisfaction if individuals do not perceive a high value or benefit from that effectiveness. Furthermore, student's personal values, goals, and priorities can impact their satisfaction.

Next, based on the test results, **H3** is accepted, which shows that perceived usefulness has a positive influence on students' satisfaction (**β = 0.419**). Most students decide to use AI applications for the specific purpose. For example, they can use these applications to access a large amount of lessons. When they realize the benefits from E-learning such as saving time, accessing course materials anytime and anywhere then their satisfaction to use these applications will increase. Indeed, earlier research by Amin et al. (2014) stated that the perceived usefulness of a mobile website had a positive and significant impact on customer satisfaction. Additionally, the research conducted by Sibona and Choi (2012) among Facebook users found out that perceived usefulness positively affected satisfaction. As a result, it is important to note that perceived usefulness from customers of a certain technology such as AI applications could eventually affect their level of satisfaction toward these applications.

In addition, **H4** —Satisfaction is positively related to students' intention to use AI applications (**β = 0.789**). If students feel satisfied with their experience using AI applications, they are likely to continue using them and explore other similar applications. According to the research by Shahijan, Rezaei, and Amin (2016), the finding shows that when students are satisfied with the university's services. Hence, the university can upgrade and improve credibility and prestige, which lead to increase the number of students as well. Satisfaction contributes to creating a positive momentum for the adoption of technology in education. Moreover, when AI provides effective, engaging, and tailored learning methods that meet users' needs, they are encouraged and motivated to continue learning and researching. As a result, when students have positive experiences with an application, they are more motivated to engage with this application over an extended period.

According to the hypothesis testing results, **H5a** and **H5c** are accepted, which show that a personal learning profile has a positive impact on perceived ease of use and perceived usefulness (**β = 0.395** and **β = 0.497**). Personal learning profile collect and analyze student's learning preferences, abilities, goals, and interests so it allows students to create their own learning profiles (Attwell, 2007). These profiles are then utilized to tailor instructional content, learning pathways, and assessments to suit the unique needs of the learner. As the content aligns closely with their habits and learning styles, students find it easier to engage with the material, leading to a heightened perception of ease of use (D'Alessandro, 2011). Furthermore, personal learning profile analyze the student's previous learning history, academic achievements, and areas of interest to deliver personalized content, resources, and learning materials that are relevant and meaningful to the student. It eliminates irrelevant information, thus preventing learners from feeling overwhelmed. It also provided appropriate learning programs, preventing feelings of boredom or frustration that may arise from standardized, one-size-fits-all approaches. This customization increases the perceived usefulness of the e-learning platform, as it will help learners improve their learning results and make more progress in learning.

By contrast, **H5b** —Personal learning profile has no significant impact on perceived effectiveness (**β = 0.137**). This conflict conclusion can be explained due to several factors. If learners realize that AI applications requires a significant amount of time and effort without offering commensurate benefits, they might not perceive effectiveness. If the teaching method is still mainly based on the presentation of knowledge through group or class instruction, the individualization of learning will be limited. Personal learning profile often require more flexible learning methods and active student participation. In Vietnam, most students study in groups rather than paying much attention to everyone. However, personal learning profile focus on personalizing learning records, which requires a more flexible learning model. In the context of Vietnam, personal learning profile will not affect the perceived effectiveness because students in higher education do not perceive much about the effectiveness that it brings.

Moreover, based on the test results**, H6a (β = 0.389**) and **H6c** (**β = 0.235**) are accepted. AI applications allow students to create their own learning environment by customizing their learning experiences such as selecting tools and resources that align with their preferences. This helps students enjoy the comfort and familiarity with the AI applications, leading to a heightened sense of ease in interacting with these technologies. Learners can use AI applications that will give students a chance to have flexibility in time, location and use the most tools to study (Daunert and Price, 2014). In addition, AI applications facilitate learners to connect to a personal learning environment with AI support to solve problems quickly and in a timely manner. For example, ChatGPT is an AI chatbot that helps learners exchange and answer questions quickly in various fields with full information and assists students to refer to wider knowledge (Levin, Fulginiti, & Moore, 2018). As a result, the personal learning environment plays an essential role in deciding the ease of use, effectiveness and usefulness of using AI applications in E-learning modules.

On the other hand, **H6b (β = -0.041**) is rejected, which means that the personal learning environment has no impact on perceived effectiveness. This can be explained because Vietnamese students are learning under the guidance of lecturers. When using AI applications to create a personal learning environment without knowing how to use it correctly, they will be confused and less effective in learning. In an individual learning environment, students can only interact and discuss with the AI chatbot. While the university environment requires a high level of teamwork, there will be problems that require interaction between students and students or students and lecturers. Therefore, although ChatGPT helps learners to answer quickly, it does not always give completely correct answers, or if users do not know how to write the correct syntax of the question, the answer will usually be general. There are also no sources of testing or faculty evaluation. Hence, students hardly feel the effectiveness of the personal learning environment.

5. Conclusion

In brief, the authors conclude with the rapid development of technology, AI can play an important role in improving the quality of education and creating a progressive learning environment. AI also provides quality knowledge through online resources. However, AI also creates many challenges related to understanding and creativity, requiring people to understand the operating mechanism and learn how to use it for the right purpose so that AI can be a useful tool for learning and human work.

5.1 Theoretical Contributions

The results of the study have strengthened and confirmed the original theory —the Technology Acceptance Model (TAM), besides expanding and adding new variables that have an impact on the intention to use AI applications (Mousavinasab et al., 2021; Sun and Gao, 2020). Based on the research results, the authors observed that students' satisfaction has the strongest impact on the intention to use. In addition to the original factors of the TAM model —perceived usefulness and perceived ease of use, our study has introduced new indicators such as perceived effectiveness, personal learning profile, and personal learning environment. Among the factors given, all factors are tested to have an impact on intention to use, especially the satisfaction factor which is considered as a mediating role between this relationship.

Additionally, the findings in our research indicate that the relationship between perceived effectiveness and satisfaction, personal learning profile and perceived effectiveness, personal learning environment and perceived effectiveness in the context of Vietnam were rejected. It turns out to be contrary to previous studies in other countries (McKenzie Montebello, 2018; Wei Wei et al., 2021). This can be considered a new discovery in the field of research concerning satisfaction and intention to use AI applications in E-learning. The contributions of this research have built a novel model that can be applied in the era of AI and enrich the studies on the intent of using AI applications.

5.2 Managerial Implications

The findings of this research can be highly beneficial for higher education institutions in Vietnam as it offers valuable insights into student perceptions and attitudes towards AI. With this knowledge, institutions can make more effective strategies to integrate AI tools into their teaching methods and learning environments. For example, institutions can collaborate with AI companies, research institutions, and other educational institutions to share knowledge, resources, and insights. Educational institutions should design AI-powered solutions that align with students' needs and preferences, thereby enhancing the overall learning experience and better understanding students' views and expectations. Besides, teachers could feel free to adopt AI-integrated teaching. They could introduce AI technology at any stage of the semester and assign any role to chatbots according to teaching needs. However, institutions need to pay more attention in checking, monitoring and preventing students from abusing AI applications in E-learning. They should conduct awareness campaigns to educate students about the risks and implications of overusing AI applications. They ought to use real-world examples to illustrate the potential harm that can result from misuse.

While AI tools can be valuable, students should remember that human judgment and critical thinking are essential, then remember to evaluate AI-generated content carefully. Additionally, learners should not blindly trust information solely because the information that is generated by AI may not be correct. They should build a solid foundation, verify facts and sources before accepting information as accurate. Besides, students should be mindful of the personal data they provide when using AI applications to avoid sharing sensitive information unless they are certain about the application's privacy practices.

Understanding the important role of satisfaction to intention to use, businesses can step up investment in improving the quality of AI applications; focusing on making these online platforms not only close to students but also target older people, in order to develop a variety of target customers. Through our research, businesses can understand students' perceptions and intentions, then adjust their AI applications to increase user satisfaction and loyalty, driving long-term business success. Applying perceived usefulness, perceived ease of use, personal learning profile and personal learning environment as criteria to develop AI applications, businesses should improve and upgrade their apps. Additionally, companies should also develop intelligent instruction design and digital platforms that use AI to provide learning, testing and feedback to identify students' gaps in knowledge and improve their academic performance.

5.3 Limitations and Future Research

Firstly, there are more variables that the study might not fully account for external factors that could influence students' perceptions and intention to use AI applications, such as individual preferences, prior experiences, or institutional support for AI integration in education. Therefore, the research topic can be expanded by pursuing new factors that are suitable for the current context so that new perspectives can be discovered. Researching some new related variables in future research can offer a more comprehensive understanding of the relationship between students' perceptions of AI applications, satisfaction, and intention to use. By addressing these suggestions in future research, scholars can contribute to a more robust and comprehensive understanding of students' perceptions of AI applications in higher education.

Additionally, in the age of artificial intelligence, teachers' and developers' perceptions will continue to play a significant role in education. However, little study was done regarding how AI applications can assist both instructors and apps developers in their roles in higher education. In that case, most of our research was conducted at the students' perceptions in e- learning AI applications. For more future research, it is advisable to be done at the instructors' and app developers' perceptions level, as AI provides many opportunities for them. The power of AI to assist both groups needs to be implemented in further research.

Lastly, to enhance the generalizability of the findings, future studies should aim to expand the number and width of samples, the scope of the survey by collecting data from multiple channels to increase rigor of the data process. This could involve students from other provinces, various universities, diverse disciplines, and different regions of the country, maybe from other countries if possible; include a wider range of students (college, undergraduates, and postgraduates' students). Moreover, replicated studies for other educational levels, other programs, and other subjects are needed to confirm the findings of this study. By doing this, the research will be more representative of the entire student population in Vietnam's higher education institutions.

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