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Factors Driving AI Adoption in English Language Learning: An Extended UTAUT2 Analysis of Vietnamese Students

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Abstract **Original Research Article**

The rapid advancement of Artificial Intelligence (AI) has transformed language education, yet limited research has explored the determinants of AI adoption among English learners in developing countries. This study investigates the key factors influencing Vietnamese students' behavioral intention and actual use of AI-powered applications in their English learning process. Drawing on an extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework, the research model incorporates seven predictors — Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit — to explain both Behavioral Intention and Use Behavior. A self-administered questionnaire was distributed to 184 Vietnamese students with prior experience using AI tools for English learning, and the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings reveal that only three factors significantly predict Use Behavior: Behavioral Intention, Facilitating Conditions, and Habit, with Behavioral Intention and Facilitating Conditions emerging as the strongest drivers. Furthermore, the study extends the existing literature by examining the combined influence of intrinsic and extrinsic personal factors on AI adoption through the lens of perceived value. These results offer practical implications for educators, edtech developers, and policymakers seeking to promote effective AI integration in English language education within the Vietnamese context.

Keywords: AI applications, learning English, behavioral intentions, UTAUT2, PLS-SEM.

1. INTRODUCTION

The development of AI has great potential for English learning, helping to increase efficiency and create customized, personalized learning experiences. In the English learning journey, AI supports learners through applications such as voice recognition, grammar correction, translation, and instant feedback. These applications allow learners to practice and improve their language skills continuously and flexibly, without relying entirely on traditional learning environments **(DaCosta & Kinsell, 2024)**. The advances in artificial intelligent have led to the development of personalized pathways in education (J. Huang et al., 2021). Learning English is becoming increasingly important in the context of globalization, with around 1.5 billion people worldwide learning English as a second language. English is not only the international language of business, science and technology, but also the main means of communication at international events and online platforms. According to the World Economic Forum, by 2050, more than half of the world's population will be able to communicate in English at a basic level, demonstrating the importance of this language in global communication and work activities **(*Shaping the Future of Learning : The Role of AI in Education 4.0 : Insight Report*, 2024)**. The increasing globalization of universities and the internationalization of student bodies have facilitated the integration of AI-based tools into educational practices **(Rahiman & Kodikal, 2024)**. Furthermore, English skills also have a positive impact on income and career opportunities. A study by Education First (EF) shows that workers with good English skills earn an average of 30-50% more than those without good English skills. This emphasizes the need to learn English to expand opportunities and improve the quality of life.

The research have published a brief research paper on the current situation of English learning at home and abroad. This study suggests that learning English, especially vocabulary, must be context-based, not on a list of vocabulary (PHÙNG VĂN ĐỆ, 2012). Students will forget all the vocabulary after the test if they don't learn the vocabulary in a certain context (Hồ Nguyên, 2024). A lack of confidence and an incorrect perception of the importance of English grammar can lead to poor academic performance. In the study of “Demotivating Factors Affecting Undergraduate Learners of Non-English Majors Studying General English: A Case of Iranian EFL Context”, the authors found that traditional teaching methods, lacking interaction and practical practice, reduced students' interest and motivation to learn **(Moiinvaziri & Razmjoo, 2014)**. According to research related to AI applications, specifically chat GPT, has impacted students' language learning process, especially in terms of learning experience, engagement, and motivation. The study is called: "Incorporating AI in foreign language education: An investigation into ChatGPT's effect on foreign language learners" (PHÙNG VĂN ĐỆ, 2012). However, the study only investigated the impact of chat GPT and only focused on students at the Non-Interventional Social Sciences Ethics Committee at Ankara Medipol University, Turkey. A 2022 study titled "Artificial Intelligence in Education (AIEd): a high-level academic and industry note 2021" also gave research on AI in education and showed that AI-based learning aids can personalize learning pathways and assessments **(Chaudhry & Kazim, 2022)**. However, the research paper does not use a specific model nor collect data and analysis. It simply uses previous research papers to illustrate and evaluate. This paper also uses the UTAUT2 model in particular based on the general view of user acceptance of a new information system of the previous 8 models. The study will specify each degree of influence on the intention to use and use behavior of AI technology for AI language learning. The analysis was based on models and data collected from students from different universities in Vietnam. From there, analyze the data and make appropriate discussions for the limits of more in-depth topics about AI in education in general and AI in English learning in particular.

Current research in Vietnam mainly focuses on the use of AI in the context of experimental or large-scale English learning. However, with the potential of AI in personalizing and improving the English learning process, this research paper will be a database for researchers in Vietnam in the future to continue to implement more extensive and developed experiments to evaluate and build AI application models suitable for each colonial context way. The new context helps to develop AI applications professionally after having accurate databases.

This study aims to apply the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model to investigate the main factors that affect on the use behavior of AI applications in learning English journey of Vietnam' students. From the factors affecting the behavioral intention and behavior of using AI in English learning of Vietnamese students, the research paper will give administrative implications that will be proposed and can be used in future research to improve service quality as well as increase efficiency and attract the use of AI and continue to use new features to create a sustainable English learning personalization roadmap. This study, hence, applies the UTAUT2 model, which will allow an in-depth analysis of related factors, such as price determination to impact the level of satisfaction and, therefore, affect process effectiveness in learning English using AI. The study also points out and exploits a lot about how the convenience and ease of use of AI can affect users' satisfaction when learning English. The current study also contributes to broadening the conceptual framework on the matter of the impact AI has on education in developing countries, such as Vietnam, which at this time is in an emergent stage in the research on new technologies. The current research in this area measured the level of AI acceptance by the UTAUT2 model, but it combined both qualitative and quantitative methods to better approach it. Data from the surveys and interviews provide a multi-dimensional perspective of opinions from both learners on how to deeply analyze factors that facilitate or impede the use of AI in English learning. For example, price can affect the satisfaction of using AI in English learning. The study contributes more profound values in an unexplored and under-researched market like Vietnam, in addition to helping to identify areas that need to be overcome to contribute to the development of future educational activities in Vietnam. This has practical implications for learners, educators and education administrators as this study really begins to realize the potential of AI in English learning pathways. The study helps to identify factors that can influence the level of satisfaction when using AI in the English learning path, thereby pointing out points that can be overcome to optimize productivity when using AI in English learning.

For learners, the study shows that AI technology meets the performance requirements in the English learning process when the results are mostly extremely positive from users, thereby opening up a new method for those who have never tried AI in their English learning path. In addition, the study also shows that the highlight of this study is the ease and convenience of use for users, as AI will almost immediately respond during the learning process. In addition, the entertainment value of learning English with AI tools is worth mentioning, the continuous interaction from AI helps to retain users and stimulate motivation in the language learning process.

2. LITERATURE REVIEW

2.1. Foundation theories of UTAUT and UTAUT2

The Unified Theory of Acceptance and Use of Technology (UTAUT) model, which mainly integrates related models and variables in different fields, was proposed by (Venkatesh et al., 2003). It mainly integrates the following eight theories: the motivational model (Davis~ et al., 1992), TAM ((Fred D, 1985); **(Venkatesh & Bala, 2008)**, the Theory of Planned Behaviour (TPB) (Ajzen, 1985), social cognitive theory **(Compeau & Higgins, 1995)**, TRA **(Martin Fishbein & Icek Ajzen, 1980)**, innovation diffusion theory **(Moore & Benbasat, 1991)**, model of PC utilisation, task-technology-fit **(Goodhue & Thompson, 1995)**, and combined TAM and TPB. UTAUT introduces four core constructs - performance expectancy, effort expectancy, social influence, and facilitating conditions - that influence behavioral intentions to use technology and/or actual use of technology (UTAUT2). This model synthesises past research and was developed based on an exhaustive review of prior technology acceptance research (Venkatesh et al., 2003). This section provides an overview of three more constructs that have been added to the UTAUT model and discusses each in detail. Hedonic motivation, price value, and habit have been added to the model as an effort to extend the current UTAUT constructs and to fill these gaps in UTAUT and to apply it more successfully to use of technology by consumers. Hedonic motivation denotes the pleasure or enjoyment derived from using a technology. While according to, price value is a person's perception of the trade-off between the financial costs of using a system and its benefits. Habit refers to the degree to which people tend to perform behaviors automatically because of learning. Hedonic motivation is defined as pleasure or enjoyment derived from using a technology. According to (Venkatesh et al., 2012), price value refers to one's perception of the trade-off between the financial costs of using a system and its benefits. Habit refers to the degree people tend to perform behaviors.

2.2. Hypotheses

2.2.1. Performance Expectancy (PEU) and Behavioral Intention (BIU)

When a customer is introduced to new information technology and gains experience using it, improved performance outcomes increase the likelihood that they will continue using the technology in the future (Venkatesh et al., 2003). PEU has also been shown to be one of the most influential factors in predicting behavioral intentation (BIU) (Venkatesh et al., 2012). In the context of this study, it can be defined as the extent to which the use of AI tools will lead to results in the pathway to personalization of English learning among Vietnamese students. Performance expectancy, or the belief that AI technology can enhance performance and productivity in educational tasks, was found to be a significant positive factor ((Romero-Rodríguez et al., 2023), **(Li & Qin, 2023)**, (Deng et al., 2023). This hypothesis is that AI will be effective in teaching when higher education educators find it beneficial for the process. Hence, the following hypothesis is formulated based on validations on these past studies:

H1: Performance expectancy (PEU) positively influences on behavioral intention (BIU) to use AI applications in English learning.

2.2.2. Effort Expectancy (EEU) and Behavioral Intention (BIU)

Effort expectancy is introduced as "the degree of ease associated with consumers' use of technology" (Venkatesh et al., 2012). As performance expectancy, effort expectancy can be found along with two more fundamental columns within the UTAUT2 predicting the indicators which influence the behavioral motives to handle and need a technology (Venkatesh et al., 2012). This shows that, before intending to use technology, users consider the necessary efforts in terms of time and effort to consider the behavior of using technology. Therefore, the following hypothesis is proposed based on prior research:

H2: Effort expectancy (EEU) positively influences on behavioral intention (BIU) to use AI applications in English learning.

2.2.3. Social Influence (SIU) and Behavioral Intention (BIU)

Social Influence is described as "the extent to which consumers perceive that important others (e.g. family and friends) believe they should use a particular technology" (Venkatesh et al., 2012). According to (Changalima et al., 2024), the study using a data model collected from 477 business students showed that, "Social influence plays a significant role in determining the behavioral intentions of business students regarding the use of ChatGPT" (Changalima et al., 2024). Accordingly, the following hypothesis has been posited:

H3: Social influence (SIU) positively influences on behavioral intention (BIU) to use AI applications in English learning.

2.2.4. Facilitating Conditions (FCU) and Behavioral Intention (BIU)

Facilitating conditions "refers to consumers" perceptions of the resources and support available to perform a behaviour" (e.g (Brown et al., 2005) (Venkatesh et al., 2012)). Facilitating conditions are also one of the four initial fundamental indicators of the original UTAUT (Venkatesh et al., 2012). Facilitating conditions may affect the intention to apply and use technology to create images (Maican et al., 2023). A study by (van Twillert et al., 2020)underscored the significance of physical infrastructure in shaping faculty attitudes toward the integration of Web 2.0 technologies into higher education. There are significant benefits to using AI, the prerequisite being that it can improve learning outcomes. Hence, the following hypothesis is formulated:

H4: Facilitating conditions (FCU) positively influence on behavioral intention (BIU) to use AI applications in English learning.

2.2.5. Hedonic Motivation (HMU) and Behavioral Intention (BIU)

Hedonic motivation has been identified as a crucial predictor variable in numerous studies within the fields of consumer behavior (**(Holbrook & Hirschman, 1982)** and information systems (Brown et al., 2005), particularly in the context of consumer technology adoption. Hedonic Motivation is described as "the fun or pleasure derived from using a technology" (Venkatesh et al., 2012). Many previous studies have shown that hedonic motivation directly influences technology adoption and is an important factor (e.g (Brown et al., 2005), (Khatimah et al., 2019)). Therefore, the hypothesis is presented as below:

H5: Hedonic motivation (HMU) positively influences on behavioral intention (BIU) to use AI applications in learning English.

2.2.6. Price Value (PVU) and Behavioral Intention (BIU)

Price Value can be described as the consumers' trade-off between the perceived benefits of the applications and the monetary cost for using them (Dodds et al., 1991). Its mean the cost to use the technology should be consistent with the technology experience worth using. Within the domain of marketing research, the perceived value of products or services is typically conceptualized as a function of both their monetary cost/price and their perceived quality (Zeithaml et al., 1988). To use the coins on them, users must feel beneficial to them. The cost and pricing structure can significantly influence consumer technology adoption. For example, the popularity of SMS in China is attributed to its low cost relative to other mobile internet applications (Yue et al., 2008). The following hypothesis is posited accordingly:

H6: Price value (PVU) positively influences on Behavioral intention (BIU) to use AI applications in learning English.

2.2.7. Habit (HBU) and Behavioral Intention (BIU)

Through the use of the UTAUT2 model to check in online flight ticket buyers, the research of "Online drivers of consumer purchase of website airline tickets" have shown that habitual behavior is an important factor influencing consumers' behavioral intentions **(Escobar-Rodríguez & Carvajal-Trujillo, 2013)**. Going back to the definition of Habit in "How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance", Habit is phrased as "the extent to which people tend to perform behaviours automatically because of learning" (Author et al., 2007). Habit has been defined as the automatic performance of behaviors due to learning (Author et al., 2007), while (Kim et al., 2005) equate habit with automaticity. Based on prior research, it is formulated the following hypothesis:

H7: Habit (HBU) positively influences on behavioral intention (BIU) of AI applications in learning English.

2.2.8. Behavioral Intention (BIU) and Use Behavior (UBU)

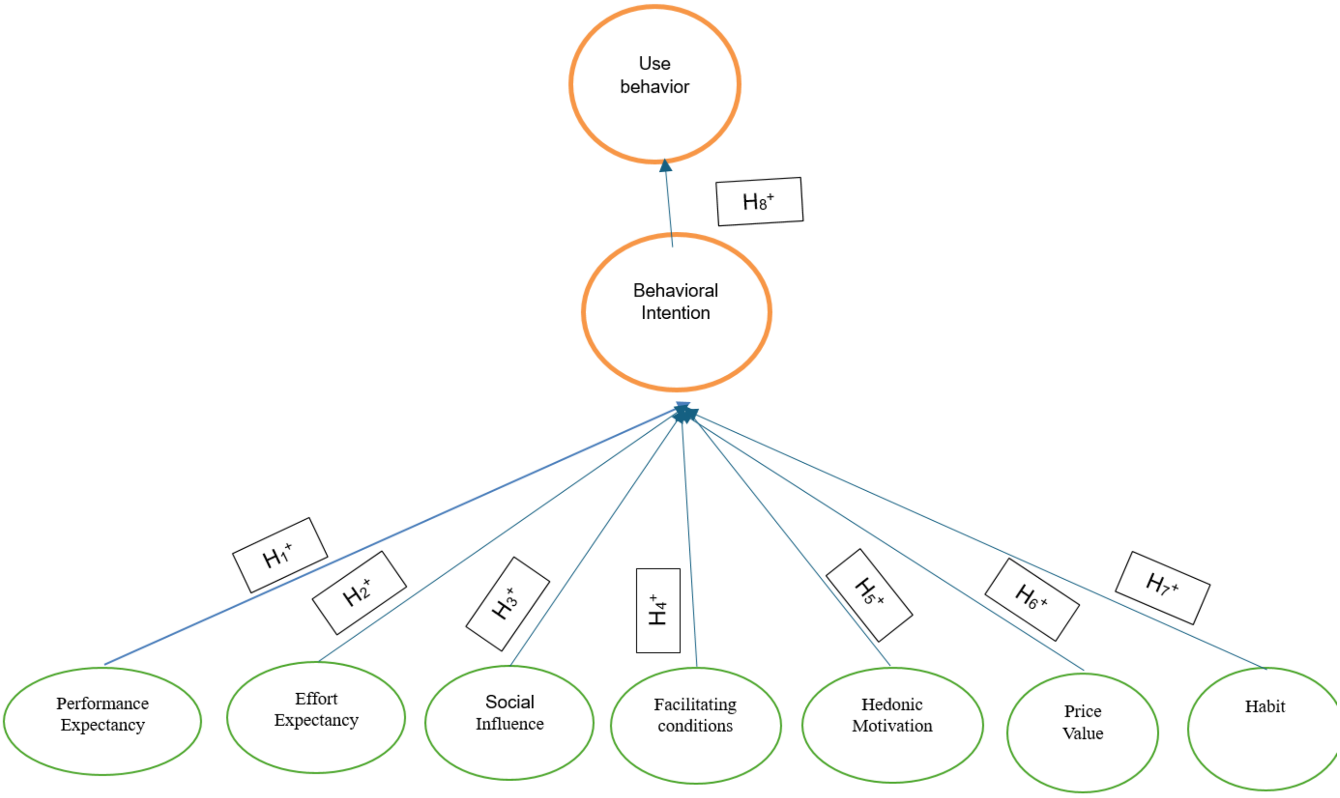
Behavioral intention as perceived attitude, and use behavior as actual action (Taylor & Todd, 1995). According to their study, user intention would affect how often they use technology (Maican et al., 2023). Direct experience will result in a stronger, more stable behavioral intention - behavior relationship **(Martin Fishbein & Icek Ajzen, 1980)**. As a result, the following hypothesis was proposed:

H8: Behavioral intention (BIU) positively influences on use behavior (UBU) of AI applications in learning English.

The hypotheses in this study are based on the UTAUT2 model along with additional factors that are appropriate to the research context. It shows that components such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and price value all have positive impacts on behavioral intention and usage behavior of AI applications in English learning. The interaction between these factors not only motivates learners to use technology but also improves the learning experience. To clarify and validate these relationships, further research is needed on the potential of AI applications in English learning.

2.3. Framework

Based on the theory and proposed research hypotheses, a research model was formed consisting of 7 relationships representing independent variables including: Performance expectancy (PEU), effort expectancy (EEU), social influence (SIU), facilitating conditions (FCU), hedonic motivation (HMU), price value (PVU) and habit (HBU) which both directly and indirectly affect the dependent variable use behavior (UBU) through intermediate variable behavioral intention (BIU) on the application of AI in the English learning process. The figure below shows the proposed research model.



Source: By author

Figure 1. Proposed model of AI application effects on English learning process

3. METHODOLOGY

3.1. Sampling method

This paper use Purposive sampling (It is one of the non-probability sampling method, also known as judgemental sampling, selective or subjective sampling, directed sampling and authoritative sampling) is a sampling technique in which researcher trusts on their own judgment when picking members of population to contribute in the study (L Sudarshan Reddy, 2016).

The goal of the study **(Mehedi Hasan Emon Graduate Student & Hassan Associate Dean, 2023)** shows the relationship between attitudes towards AI and behavioral intentions to use ChatGPT. The study uses variables in the UTAUT2 model and research questions to explore the relationship between these variables. Therefore, the group has been conducted in this study with these criteria before conducting a survey among students about learning English through AI. Surveys are distributed through a variety of online platforms, such as social media, email, and online forums.

3.2. Method analysis (PLS-SEM)

Partial least squares structural equation modeling (PLS-SEM) has become a popular method for estimating path models with latent variables and their relationships. A common goal of PLS-SEM analyses is to identify key success factors and sources of competitive advantage for important target constructs such as customer satisfaction, customer loyalty, behavioral intentions, and user behavior **(Martin Fishbein & Icek Ajzen, 1980)**.

According to the research paper "AI-Based Chatbots Adoption Model for Higher-Education Institutions: A Hybrid PLS-SEM-Neural Network Modelling Approach" (Mohd Rahim et al., 2022), PLS-SEM in the research paper on the application of AI Chatbots implements model validation and evaluation of effective hypotheses. Notably, PLS-SEM provides more accurate predictions than most traditional regression techniques. Based on the above study, this paper uses PLS-SEM to evaluate the reliability and validity of variable indicators. Next, PLS-SEM is used to identify the key factors influencing the behavior of using AI applications in the English learning process among students, leveraging both linear and non-linear interactions in the proposed model. Given the presence of multiple interaction terms within our proposed model, we opted to utilize partial least squares (PLS) as our primary analytical technique. PLS is a robust statistical method capable of handling complex structural equation models, as demonstrated by **(Editors Janice DeGross Sirkka Jarvenpaa Ananth Srinivasan & Chin Barbara L Marcolin Peter R Newsted, 2003)**.

3.3. Sample size

Determining the sample size is an important step in research on AI applications in English learning, ensuring the accuracy and reliability of research results. In addition, through the calculator by Daniel Soper, which is suggested by the recommend minimum sample size is 184. The following settings were made in the calculator:

Anticipated effect size - 0.3

Desired statistical power level - 0.8

Probability level - 0.05

Number of latent variables - 9

Therefore, from the justification above, the minimum sample size usable for data analysis comprised at least 184 responses to be able to meet the analysis in the next sections.

3.4. Questionnaire research

Google Forms is an intuitive online form-making tool for creating online surveys and comes absolutely free of charge. Its interface is so easy to work with, having options to make questions multiple-choice, with checkboxes, or just as an open question. With Google Forms, responses are automatically structured into a spreadsheet for tracking responses. The fact that it links data directly into google sheets means it will also make analysis easier and at no extra cost. The questionnaires in this research included 10 sections, with the first being the demographic one, followed by the variables of study: Performance expectancy, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, behavioral intention, use behavior.

Using a 7-point likert scale has many advantages in conducting survey research, such a scale allows respondents to express their agreement or disagreement with a more precise way, from strongly positive to strongly negative. This reduces the tendency to choose neutral points and maximizes the reliability of the data collected, accurately collected data will help the research objectives to be effective and reliable. The scale will include Strongly disagree, disagree, slightly disagree, neutral, slightly agree, agree, strongly agree.

4. RESULT ANALYSIS

4.1. Demographics

Table 1. Demographic profile of respondents

Demographic characteristic		Frequency	Percentage
Gender	Female	119	64%
	Male	67	36%
Year	Freshman	9	4,8%
	Sophomore	47	25,3%
	Junior	39	21%
	Senior	91	48,9%
Monthly income	<VND 5,000,000	107	57,5%
	VND 5,000,000 – VND 10,000,000	55	29,6%
	VND 10,000,000 – VND 20,000,000	20	10,8%
	>VND 20,000,000	4	2,2%
How often do you use AI to learn English?	Always	30	16,1%
	Usually	78	41,9%
	Sometimes	71	38,2%
	Never	7	3,8%

Source: By the author

As Table 1 shows, women accounted for 64% of the total 186 samples and men accounted for 36% with 67 samples. In addition, there was diversity among the respondents, with the largest proportion being fourth-year students with 91 samples and accounting for 48.9%, followed by second-year students with 25.3%, third-year students with 21% and the lowest being first-year students with 9 samples and accounting for 4.8%. Income in the data also has a significant difference, with income <5,000,000 accounting for more than half with 57.5%, income from VND 5,000,000 - VND 10,000,000 accounting for about 29.6%, income from VND 10,000,000 - VND 20,000,000 accounting for about 10.8% and the rest is >VND 20,000,000 accounting for about 2.2% with 4 data. The majority of the data shows that the frequency of using AI in learning English is regular with 41.9% and occasional is 38.2%, in addition, there are 30 data showing that they use it regularly, accounting for about 16.1%.

4.2. Common Method Bias (CMB)

To address the potential concerns regarding common method bias (CMB), we implemented a range of methodological strategies, drawing upon the insights provided by previous studies (Low et al., 2023) and **(Tan & Ooi, 2018)**. All items in the scale were measured by a single questionnaire survey, and there is a possibility that the examined relationships between constructs may be distorted by the effects of common method bias, a serious problem that can potentially jeopardize the validity of research results (Spector et al., 2019).

The bias created by common method bias, known as common method bias, occurs when the estimated relationship between one construct and another may be inflated. Therefore, the author used data screening and statistical procedures, from which he analyzed the individual variables and tested the VIF index. And the statistical results obtained were that all VIF coefficients were less than 5. Therefore, this common method bias problem is unlikely to occur with this data set (Spector et al., 2019).

4.3. Assessment Outer Model

Prior to testing the hypotheses proposed in the structural model, it is essential to evaluate and validate the measurement model. This involves assessing both the reliability and validity of the measurement items (Joseph F. Hair, 2017). To assess reliability, three commonly used measures were employed: Cronbach's Alpha (CA), composite reliability (CR), and Dijkstra-Henseler's rho (ρA) (Teo et al., 2015). When running data on outer loading, data of variable FCU2 (0.458) < 0.7, UBU2 (0.7), UBU1 (0.661) < 0.7, remove variable FCU2, UBU2, UBU1 to run the data again. The results, presented in Table 4.4, indicate that the minimum values for CA, ρA and CR were 0.822, 0.826, and 0.894, respectively. The values obtained for Cronbach's Alpha (CA), composite reliability (CR), and Dijkstra-Henseler's rho (ρA) were all found to be greater than the recommended threshold of 0.7 (Foo et al., 2018).

This indicates that the measurement model exhibits satisfactory reliability for all constructs. As shown in Table 4.4, the minimum AVE value (0.644) exceeded the 0.5 threshold, and all factor loadings (0.728-0.908) surpassed 0.7 (Binh et al., 2024; T.-Q. Dang et al., 2026; Joseph F. Hair, 2017);. This confirms the convergent validity of the study. Convergent validity was determined based on the extracted average variance (AVE) (T. Dang et al., 2023). Discriminant validity was assessed using Fornell-Larcker's criterion and cross-loadings **(Fornell & Larcker, 1981)**, **(T.-Q. Dang, Nguyen, & Duc, 2025; Henseler et al., 2015)**. As shown in Table 4.5, the square root of each Average Variance Extracted (AVE) value exceeds the corresponding correlation coefficient with any other construct (Henseler et al., 2015; Le et al., 2025; Tran et al., 2025). Additionally, the cross-loadings presented in Table 4.6 indicate that each item loads more strongly on its respective construct than on any other construct. These findings collectively confirm the discriminant validity of the measurement model.

Table 2. Convergent Validity and Construct Reliability

Constructs	Items	Factor Loadings (FL)	Cronbach's Alpha (CA)	Dijkstra Henseler rho_A (pA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
BIU	BIU1	0.858	0.899	0.901	0.93	0.768
	BIU2	0.888				
	BIU3	0.883				
	BIU4	0.874				
EEU	EEU1	0.825	0.862	0.876	0.9	0.644
	EEU2	0.728				
	EEU3	0.779				
	EEU4	0.844				
	EEU5	0.831				
FCU	FCU1	0.863	0.874	0.887	0.913	0.725
	FCU3	0.872				
	FCU4	0.844				
	FCU5	0.825				

HBU	HBU1	0.814	0.9	0.904	0.926	0.715
	HBU2	0.867				
	HBU3	0.831				
	HBU4	0.872				
	HBU5	0.841				
HMU	HMU1	0.859	0.875	0.881	0.914	0.727
	HMU2	0.857				
	HMU3	0.836				
	HMU4	0.856				
PEU	PEU1	0.870	0.912	0.914	0.932	0.695
	PEU2	0.856				
	PEU3	0.816				
	PEU4	0.783				
	PEU5	0.867				
	PEU6	0.805				
PVU	PVU1	0.825	0.858	0.866	0.904	0.702
	PVU2	0.891				
	PVU3	0.849				
	PVU4	0.783				
SIU	SIU1	0.854	0.878	0.885	0.916	0.732
	SIU2	0.908				
	SIU3	0.827				
	SIU4	0.829				
UBU	UBU3	0.816	0.822	0.826	0.894	0.738
	UBU4	0.888				
	UBU5	0.872				

Source: By the authors

Table 3. Fonell-lacker criterion

Latent Construct	BIU	EEU	FCU	HBU	HMU	PEU	PVU	SIU	UBU
BIU	0.876								
EEU	0.713	0.802							
FCU	0.691	0.699	0.851						
HBU	0.74	0.747	0.563	0.845					
HMU	0.726	0.766	0.765	0.66	0.852				
PEU	0.719	0.807	0.746	0.643	0.833	0.833			
PVU	0.728	0.769	0.722	0.731	0.748	0.731	0.838		
SIU	0.62	0.735	0.642	0.663	0.715	0.695	0.678	0.855	
UBU	0.695	0.669	0.651	0.647	0.615	0.616	0.697	0.527	0.859

Source: By the author

4.4. Assessment Inner Model

4.4.1. Assessing the Structural Model

To ensure the robustness of the study's findings, the authors first addressed the potential issue of multicollinearity. This statistical phenomenon, where independent variables are highly correlated with each other, can distort the regression model's results. To mitigate this risk, a collinearity test was conducted, as suggested by (Le et al., 2025; Phan et al., 2025). The results, presented in Table 4.3, revealed that the Variance Inflation Factor (VIF) values for all independent variables ranged from 1.205 to 3.155. As these values are well below the commonly accepted threshold of 5.0 (A.-H. D. Nguyen et al., 2024; Tien et al., 2023), the authors concluded that multicollinearity was not a significant concern in this study. Subsequently, the authors employed a bootstrapping procedure to enhance the reliability of the inferential statistics. This technique involves drawing multiple random samples (5,000 in this case) with replacement from the original dataset. By analyzing these subsamples and calculating confidence intervals, bootstrapping can provide more accurate estimates, especially when dealing with smaller sample sizes or non-normally distributed data. The results of the hypothesis testing, summarized in Table 4, shed light on the relationships between the variables. Notably, the findings revealed that EEU, FCU, HBU, HMU, PEU, PVU, SIU, and BIU all have a significant impact on UBU. This supports Hypotheses H4, H7, and H8.

However, the relationship between EEU and BIU, as hypothesized in H2, was not statistically significant. The p-value of 0.981, which is substantially greater than the significance level of 0.05, indicates a lack of evidence to support this hypothesis. Similarly, Hypotheses H1, H3, H5, and H6 were also not supported, as the associated p-values did not fall below the 0.05 threshold.

Table 4. Hypotheses testing

Hypotheses	PLS Path	Original Sample (O)	Sample mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values (p)	Remark
H8	BIU→UBU	0.672	0.677	0.052	12.85	0	Supported
H2	EEU→BIU	-0.002	-0.005	0.101	0.023	0.981	Unsupported
H4	FCU→BIU	0.17	0.174	0.085	2.008	0.045	Supported
H7	HBU→BIU	0.369	0.371	0.089	4.133	0	Supported
H5	HMU→BIU	0.153	0.152	0.116	1.317	0.188	Unsupported
H1	PEU→BIU	0.168	0.168	0.097	1.73	0.084	Unsupported
H6	PVU→BIU	0.134	0.132	0.103	1.303	0.193	Unsupported
H3	SIU→BIU	-0.053	-0.052	0.09	0.587	0.557	Unsupported

Source: By SmartPLS 4

For supported variables such as BIU, FCU, HBU to BIU, the higher the Original Sample (O), the stronger the impact on the relationship between them. Therefore, hypotheses 8 with Original Sample 0.672, shows that the relationship between behavioral intention will have the strongest impact on use behavior in the context of a survey of 184 people on the use of AI in English learning among Vietnamese students.

4.4.2. The Predictive Relevance and R-square overview

The study utilized a blindfolded cross-validation technique to compute the Q^2 value, a measure of a model's predictive accuracy. According to (Joseph F. Hair, 2017), a positive Q^2 value signifies the model's ability to predict future outcomes. The Q^2 value derived from our analysis (Table 6, column Q^2) was positive, confirming the model's predictive relevance (Dang et al., 2026; Phan et al., 2025).

Table 6. Relevance (Q^2)

Endogenous variable	Q^2 (=1-SSE/SSO)	Predictive Relevant
BIU1	0.433	$Q^2>0$
BIU2	0.442	$Q^2>0$
BIU3	0.525	$Q^2>0$
BIU4	0.544	$Q^2>0$
UBU3	0.302	$Q^2>0$
UBU4	0.377	$Q^2>0$
UBU5	0.445	$Q^2>0$

Source: By SmartPLS4

Additionally, to establish a minimum level of explanatory power, the R^2 value, a measure of the proportion of variance explained by the model, must exceed 0.1 (Loh et al., 2021). In our study, the lowest R^2 value was 0.482, surpassing the threshold and indicating a substantial explanation of variance in the target endogenous construct. From the R-square data, we can see the level of explanation of 7 variables: Performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit for the model. The above variables explain 68.9% of the influence on the Behavioral Intention variable of AI applications on learning English journey in Vietnam' students. In addition, the behavioral intention variable explains 48.2% of the influence on use behavior. In other words, behavioral intention affects 48.2% on use behavior when students use AI for learning English.

5. DISCUSSION

5.1. Performance Effort (PEU) Unsupported Behavioral Intention (BIU)

The purpose of the study is to find out the mutual influence of variables, to determine whether there is mutual support between variables or not. First, in the case of the performance expectation variable, the behavioral intention variable in using AI to learn English may stem from the reason that students do not really understand how AI can improve their English and the great benefits that AI brings from using it (Piarna et al., 2020). In addition, there are special cases where students have experienced using AI in learning but did not get the desired results, thereby reducing expectations and not continuing to use the behavior. On the other hand, it may stem from students' needs to use traditional learning methods and only see AI as a supporting tool rather than a main factor.

5.2. Effort Expectation (EEU) Unsupported Behavioral Intention (BIU)

The effort expectation variable does not support the behavorial intention variable. The reason is determined to be due to the current technological proficiency of students, they have experienced and gradually become familiar with various types of technology, so they do not consider AI in learning English as a complex and difficult tool to use **(Sucahyo & Ardyan, 2022)**. In addition, another reason mentioned is that the attractiveness in the process of using AI to learn English, can make students willing to experiment without worrying about the efforts when using it. The lack of education and guidance from schools also makes students feel that using AI is easy and does not require much effort, because they only use basic programs without being guided to explore more about other features and make the most of AI.

5.3. Social Influence (SIU) Unsupported Behavioral Intention (BIU)

The results also show that social influence unsupports behavorial intention, the objective cause may come from the fact that students have a high sense of personal learning, so they are less influenced by the opinions of those around them. In addition, we can also consider the factors surrounding students, for example, friends around them do not use AI to learn English, students can study in an environment that does not emphasize technology more than traditional learning.

5.4. Facilitating Conditions (FCU) Supported Behavioral Intention (BIU)

The transformation of facilitating conditions support for behavioral intention comes from the fact that technology support tools are becoming more and more popular and widespread such as smartphones, internet, ... helping students without technological barriers, thereby using AI more in learning English (Nur et al., 2021). In addition, the convenience and coverage of AI on different devices and platforms, when students know they can learn with AI on both phones and computers, they will tend to use it anytime, anywhere. To be able to transform Facilitating conditions support for Behavioral Intention into something stronger, you can consider applying it to your current learning path on a daily basis, then using the tool will gradually become a learning habit and turn it into an indispensable part of life.

5.5. Hedonic Motivation (HMU) Unsupported Behavioral Intention (BIU)

The results of Table 5 show that hedonic motivation (HMU) does not significantly support to behavioral intention (BIU). This suggests that although users may find AI applications interesting for learning English, this factor is not enough to promote long-term usage intention or increase the frequency of use. According to the Technology Acceptance Model (TAM) and the Uses and Gratifications Theory, entertainment motivation is often thought to create short-term satisfaction but does not necessarily lead to users returning to the platform repeatedly or maintaining sustainable usage intention (Fred D. Davis, 2013). This result is consistent with some previous studies showing that entertainment motivation tends to promote usage intention when accompanied by additional factors such as usefulness or convenience, while entertainment alone does not ensure sustainability in usage intention **(Lim & Ting, 2012)**. In addition, the entertainment motivation factor may also be dominated by other external factors, such as content quality or app interactivity, thus reducing the direct impact of HMU on BIU **(Sledgianowski & Kulviwat, 2009)**.

5.6. Price Value (PVU) Unsupported Behavioral Intention (BIU)

Price value (PVU) does not have a significant impact on behavioral intention (BIU) in using AI applications to support English learning. This indicates that, although cost may be important in the initial decision to use, it is not the main factor driving long-term usage intention. In the educational field, especially language learning, users often prioritize factors such as efficiency, personalization, and content quality over price.

According to the UTAUT2 model, price value only has an impact when users perceive that the cost is appropriate for the benefits received. However, with AI applications in education, users' perceived value largely comes from the ability to provide personalized content and continuous learning support 24/7. Reaseach by (Venkatesh et al., 2012) emphasized that factors such as usefulness and positive experience often have a greater influence on long-term usage intention, especially in modern technological systems.

5.7. Habit (HBU) Supported Behavioral Intention (BIU)

The results in Table 5 show that habit (HBU) has a positive impact on the behavioral intention (BIU) of AI applications in the English learning journey of the respondents. Consumers who are less sensitive to context or have limited cognitive capacity are more likely to rely on established habits to guide their behavior (Verplanken et al., 2006). This means that when the use of AI applications becomes a daily habit, the intention to continue using these technologies will be strengthened more strongly. In the process of learning a foreign language, regular repetition and the formation of learning habits are important factors that help maintain motivation and improve learning efficiency. According to (Kim et al., 2005), habit can play an important role in strengthening the intention to use technology, because when technology becomes part of the habit, users tend to rely on it more to achieve learning goals.

According to "Empirical investigation of factors influencing consumer intention to use an artificial intelligence-powered mobile application for weight loss and health management", Habit emerged as the most significant independent variable in predicting user intention **(C. Y. Huang & Yang, 2020)**. In addition, the habit of using AI applications can help Vietnamese students gradually become familiar with the interface, features, and personalized learning paths, increasing their comfort and trust in this technology. Research by (Author et al., 2007) confirmed that habit can reduce the barrier from novelty, thereby making learners less likely to use AI applications, and thereby increasing their intention to continue using them. This suggests that educational application developers should facilitate learners to form daily usage habits, such as providing periodic learning reminders, establishing clear pathways, and encouraging learning progress-tracking activities.

5.8. Behavioral Intention (BIU) Supported Use Behavior (UBU)

The results of the study show that BIU has a positive impact on the actual UBU of AI applications in the English learning journey of Vietnamese students. This suggests that when students have a strong intention to use, they are more likely to engage in actual use behavior. In language learning applications, intention to use is driven by many factors, including belief in the ability to improve English skills, convenience, and personalized features that AI technology brings (Venkatesh et al., 2003.). As this intention is reinforced, students tend to use AI applications more frequently, which creates a cycle that encourages continued use.

The transformation from intention to actual behavior can also be explained by (Ajzen, 1991) theory of planned behavior (TPB), which argues that intention to use is the strongest predictor of behavior. According to this theory, when students feel that using AI applications will help improve their English ability, it not only increases their intention to use but also leads to actual action. In addition, frequent use of AI applications can also form a habit and strengthen future intention to use, forming a cycle that encourages long-term use.

6. Implications

6.1. Theoretical Implications

Firstly, this study delves into the adoption of Artificial Intelligence (AI) in a university setting, aiming to validate and extend the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model in this specific context. By examining the factors influencing AI adoption behavior among Vietnamese students during their English language learning, this study contributes to a deeper understanding of the underlying mechanisms driving technology adoption in higher education.

Our findings confirm the flexibility and robustness of the UTAUT2 model in explaining the adoption of emerging technologies. The core constructs of the model, including Facilitating Conditions, Habits, and Behavioral Intentions, are found to be significant predictors of AI adoption intention and behavior. However, the relative importance of these factors varies across different user groups, highlighting the need for a nuanced approach to understanding technology adoption in diverse contexts.

A further critical extension of the UTAUT2 model to consumer contexts involves the consideration of facilitating conditions. While the original UTAUT2 framework proposed a direct causal relationship between facilitating conditions and actual behavior, our theoretical model posits that these conditions, moderated by the demographic factors of gender and age, also exert a significant influence on behavioral intentions. Empirical analysis revealed that the impact of facilitating conditions on behavioral intention is particularly pronounced for older women, who tend to perceive the availability of resources, knowledge, and support as essential prerequisites for the adoption of new technologies (T.-Q. Dang, Nguyen, Tran, et al., 2025; L.-T. Nguyen et al., 2025; Venkatesh et al., 2012).

Furthermore, this study extends the existing body of knowledge by categorizing the most common perceptions and attitudes towards AI applications in higher education. The results show that positive perceptions of AI, along with facilitating conditions and the development of habits related to AI use, significantly influence the adoption of these technologies in English language learning among university students in general and students in Vietnam in particular.

Secondly, from a theoretical perspective, this study supports the applicability of the UTAUT2 model in higher education and contributes to a more comprehensive understanding of the determinants of AI adoption in this specific field. The findings suggest that while UTAUT2 provides a solid foundation for explaining technology adoption, additional factors or extensions to the model may be necessary to capture the complexity of human behavior and the unique characteristics of AI technology.

Ultimately, this study provides valuable insights for policy makers, educators, and technology developers in higher education, especially in Vietnam. By understanding the factors that influence AI adoption, institutions can develop effective strategies to promote the integration of AI into English language learning across teaching, learning, and administrative processes. This study contributes to the previous literature with a more multidimensional perspective of theories when examining the impact of PEU, EEU, SIU, FCU, HMU, PVU, and HBU on UBU through BI. As a result, this study has contributed to the literature on AI chatbots a new finding that Facilitating conditions, Habits and Behavioral Intentions of students influence their English learning through AI applications. While the remaining factors (PEU, EEU, SIU, HMU, PVU) do not have a strong influence on the behavior of using English learning through AI applications in Vietnamese students.

6.2. Managerial Implications

This study’s findings offer valuable guidance to higher education institutions seeking to optimize the integration of AI technologies into English language instruction and administrative functions.

Firstly, this study identifies crucial factors influencing the adoption of AI technologies for English language learning among Vietnamese students, thereby providing valuable insights for the development of effective implementation strategies. Organizations can formulate initiatives that emphasize the advantages of AI, enhance user experiences, and cultivate habits that encourage the utilization of AI in English language learning.

Secondly, the findings of this study indicate that businesses should allocate greater emphasis on utility values, such as enhanced ease of use, rather than hedonic value when developing AI applications for English language learning. By prioritizing these utility values, businesses can establish a sustainable competitive advantage and stimulate customer adoption (Hanifa et al., 2023).

Thirdly, when developing AI-related service systems, service providers must exercise caution in providing appropriate information to facilitate seamless integration into English language learning applications. This is crucial as it directly influences users' intention to utilize AI for English language learning. Fourthly, behavioral intention to use AI constitutes a significant factor contributing to the formation of users' behavior in the context of English language learning via AI applications. Furthermore, if users perceive a negative correlation between the frequency of AI usage and their future commitment to a particular AI application, they are more likely to adopt a more objective evaluation approach. This, in turn, enables service providers to offer more favorable conditions for users to engage in English language learning through AI.

Additionally, AI applications can be very useful, but if it is not easy to use or not personalized, users will still not use it regularly. To create novelty in using AI for English learning, users need to participate in seminars and workshops related to introducing AI in a simple, easy-to-understand way, emphasizing the specific benefits that AI brings to English learning. From there, users will be encouraged to form habits that lead to the intention to use AI to learn English long-term in the future.

Finally, to facilitate faculty professional development, it is recommended that institutions offer courses on AI applications in education, establish communities of practice to foster knowledge sharing, and integrate AI competencies into faculty development standards. To ensure the ethical use of AI in English language research and teaching, it is recommended that institutions implement measures to encourage students to harness the potential benefits of AI.

7. Conclusion and suggestion for further researches

The application of artificial intelligence (AI) in the English learning process of Vietnamese students is gradually becoming an important trend and bringing many positive impacts. AI technology supports personalizing the learning path, optimizing time, and improving the necessary skills for learning English, helping learners access effective learning materials and methods, suitable for their level. Research results show that factors such as usage habits, performance expectations, ease of use expectations, and positive experiences play an important role in promoting the intention to use and actual usage behavior of AI applications. This indicates that when students have formed habits and realized the effectiveness of applying AI to English learning, they tend to continue using it and see it as an indispensable part of their learning journey. Although the price value factor did not significantly influence the intention to use, this result emphasizes that Vietnamese students care more about the quality and effectiveness of learning tools than the initial cost. This also reflects the increasing trend of students valuing the learning experience, as they are willing to invest in tools that bring real value and help them achieve their long-term language learning goals. At the same time, the presence of AI not only changes the way students learn but also significantly improves the level of motivation, as students receive timely support and detailed feedback on their progress. Therefore, AI not only acts as a learning tool but also as a motivator to promote persistence and maintain long-term learning intentions.

To fully exploit the potential of AI in English learning, application developers should focus on optimizing the user experience through personalized features, friendly interface design, and providing quality learning materials. At the same time, AI applications need to be integrated with teaching methods that suit the learning style of Vietnamese people, ensuring compatibility with the curriculum and the requirements of learners. Emphasizing these factors not only helps attract students' interest and increase their intention to use but can also reduce barriers and help learners adapt to technology more easily. In the future, combining AI with traditional teaching methods will open up new directions, bringing richer and more comprehensive learning experiences to Vietnamese students. This not only creates a positive learning environment but also helps students equip themselves with the necessary skills in the digital age, supporting them to access many opportunities for development and integration into the international environment. The harmonious combination of AI technology and traditional education will likely create a breakthrough in the field of language training, bringing sustainable benefits to learners in conquering English as well as building a solid knowledge foundation for the future.

REFERENCES

Ajzen, I. (1985). *From Intentions to Actions: A Theory of Planned Behavior IcekAjzen*.

Ajzen, I. (1991). *The Theory of Planned Behavior*.

Author, C., Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2007). How Habit Limits the Predictive Power of Intention: The Case of Information Systems. In *Source: MIS Quarterly* (Vol. 31, Number 4). http://www.jstor.orgStableURL:http://www.jstor.org/stable/25148817

Binh, N. T. H., Dang, T.-Q., & Nguyen, L.-T. (2024). Metaverse: The Future for Immersive Logistics and International

Business Education. *Journal of Teaching in International Business*, *35*(3–4), 75–107. https://doi.org/10.1080/08975930.2024.2445861

Brown, S. A., Venkatesh, V., Allen, J., & Hu, P. (2005). Model of Adoption of Technology in Households: A Baseline Model Test and Extension Incorporating Household Life Cycle Households: A Baseline Model Test and Extension Incorporating Household Life Cycle1. In *Source: MIS Quarterly* (Vol. 29, Number 3).

Changalima, I. A., Amani, D., & Ismail, I. J. (2024). Social influence and information quality on Generative AI use among business students. In *The International Journal of Management Education* (Vol. 22, Number 3). Elsevier. https://doi.org/10.1016/J.IJME.2024.101063

Chaudhry, M. A., & Kazim, E. (2022). Artificial Intelligence in Education (AIEd): a high-level academic and industry note 2021. *AI and Ethics*, *2*(1), 157–165. https://doi.org/10.1007/s43681-021-00074-z

Compeau, D. R., & Higgins, C. A. (1995). Application of social cognitive theory to training for computer skills. *Information Systems Research*, *6*(2), 118–143. https://doi.org/10.1287/isre.6.2.118

DaCosta, B., & Kinsell, C. (2024). Investigating Media Selection through ChatGPT: An Exploratory Study on Generative Artificial Intelligence in the Aid of Instructional Design. *Open Journal of Social Sciences*, *12*(04), 187–227. https://doi.org/10.4236/jss.2024.124014

Dang, T., Tan, W.-H., Aw, C.-X., & Ooi, K.-B. (2023). *How to generate loyalty in mobile payment services? An integrative dual SEM-ANN analysis*.

Dang, T.-Q., Mai, V.-T. L., Duc, D. T. V., Huynh, T. B., & Nguyen, N. T. T. (2026). A mixed methods analysis of palm payment adoption based on UTAUT2 and perceived trust. *Discover Psychology*. https://doi.org/10.1007/s44202-025-00548-9

Dang, T.-Q., Mai, V.-T. L., Duc, D. T. V., Huynh, T. B., & Nguyen, N. T. T. (2026). A mixed methods analysis of palm payment adoption based on UTAUT2 and perceived trust. *Discover Psychology*. https://doi.org/10.1007/s44202-025-00548-9

Dang, T.-Q., Nguyen, L.-T., & Duc, D. T. V. (2025). Impulsive Buying and Compulsive Buying in Social Commerce: An Integrated Analysis using the Cognitive-Affective-Behavior Model and Theory of Consumption Values with PLS-SEM. *SAGE Open*, *15*(2). https://doi.org/10.1177/21582440251334215

Dang, T.-Q., Nguyen, T.-M., Tran, P.-T., Phan, T.-T. C., Huynh, T.-B., & Nguyen, L.-T. (2025). From reality to virtuality: Unveiling Gen Z's purchasing behavior through virtual influencers in the metaverse. *Digital Business*, *5*(2), 100141. https://doi.org/10.1016/j.digbus.2025.100141

Davis~, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and Intrinsic Motivation to Use Computers in the Workplace'. In *Journal of Applied Social Psychology* (Vol. 22).

Deng, P., Chen, B., & Wang, L. (2023). Predicting students' continued intention to use E-learning platform for college English study: the mediating effect of E-satisfaction and habit. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1182980

Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of Price, Brand, and Store Information on Buyers' Product Evaluations. In *Source: Journal of Marketing Research* (Vol. 28, Number 3).

Editors Janice DeGross Sirkka Jarvenpaa Ananth Srinivasan, O. I., & Chin Barbara L Marcolin Peter R Newsted, W. W. (2003). *PROCEEDINGS OF THE SEVENTEENTH*

INTERNATIONAL CONFERENCE ON INFORMATION SYSTEMS A PARTIAL LEAST SQUARES LATENT VARIABLE MODELING APPROACH FOR MEASURING INTERACTION EFFECTS: RESULTS FROM A MONTE CARLO SIMULATION STUDY AND VOICE MAIL EMOTION/ADOPTION STUDY.

Escobar-Rodríguez, T., & Carvajal-Trujillo, E. (2013). Online drivers of consumer purchase of website airline tickets. *Journal of Air Transport Management*, *32*, 58–64. https://doi.org/10.1016/j.jairtraman.2013.06.018

Foo, P. Y., Lee, V. H., Tan, G. W. H., & Ooi, K. B. (2018). A gateway to realising sustainability performance via green supply chain management practices: A PLS–ANN approach. *Expert Systems with Applications*, *107*, 1–14. https://doi.org/10.1016/J.ESWA.2018.04.013

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. In *Source: Journal of Marketing Research* (Vol. 18, Number 1).

Fred D. (1985). *A TECHNOLOGY ACCEPTANCE MODEL FOR EMPIRICALLY TESTING NEW END-USER INFORMATION SYSTEMS: THEORY AND RESULTS*.

Fred D. Davis. (2013). *Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology*.

Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual Performance. In *Source: MIS Quarterly* (Vol. 19, Number 2).

Hanifa, R., Adam, M., Isnurhadi, & Andriana, I. (2023). DOES COMPETITIVE ADVANTAGE, OPERATING EFFICIENCY AND INTELLECTUAL CAPITAL EFFECT SUSTAINABLE COMPETITIVE ADVANTAGE (SCA)? *Journal of Law and Sustainable Development*, *11*(3). https://doi.org/10.55908/sdgs.v11i3.463

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hồ Nguyên. (2024). *NGHIÊN CỨU ẢNH HƯỞNG CỦA CÔNG CỤ TRÍ TUỆ NHÂN TẠO ĐỐI VỚI QUÁ TRÌNH TỰ HỌC TIẾNG ANH CỦA SINH VIÊN NGÀNH NGÔN NGỮ ANH, TRƯỜNG ĐẠI HỌC NGOẠI NGỮ, ĐẠI HỌC ĐÀ NẴNG*.

Holbrook, M. B., & Hirschman, E. C. (1982). *The Experiential Aspects of Consumption: Consumer Fantasies, Feelings, and Fun*. http://jcr.oxfordjournals.org/

Huang, C. Y., & Yang, M. C. (2020). Empirical investigation of factors influencing consumer intention to use an artificial intelligence-powered mobile application for weight loss and health management. *Telemedicine and E-Health*, *26*(10), 1240–1251. https://doi.org/10.1089/tmj.2019.0182

Huang, J., Saleh, S., & Liu, Y. (2021). A review on artificial intelligence in education. *Academic Journal of Interdisciplinary Studies*, *10*(3), 206–217. https://doi.org/10.36941/AJIS-2021-0077

Joseph F. Hair, C. L. H. A. B. R. A. Y.-L. C. (2017). *An updated and expanded assessment of PLS-SEM in information systems research. Industrial Management and Data Systems* (Vol. 87). https://doi.org/https://doi.org/10.1108/IMDS-04-2016-0130

Joseph Hair, B. B. R. A. W. B. (2019). *Multivariate Data Analysis* (Vol. 87).

Khatimah, H., Pertamina, U., Susanto, P., Negeri, U., Nor, P., & Abdullah, L. (2019). HEDONIC MOTIVATION AND SOCIAL INFLUENCE ON BEHAVIORAL INTENTION OF E-MONEY: THE ROLE OF PAYMENT HABIT AS A MEDIATOR.

In *International Journal of Entrepreneurship* (Vol. 23, Number 1).

Kim, S. S., Malhotra, N. K., & Narasimhan, S. (2005). Two competing perspectives on automatic use: A theoretical and empirical comparison. *Information Systems Research*, *16*(4), 418–432. https://doi.org/10.1287/isre.1050.0070

L Sudarshan Reddy, K. R. (n.d.). *Justifying The Judgmental Sampling Matrix Organization in Outsourcing Industry*.

Le, T.-T., Lin, P.-T., Duc, D. T. V., Dang, T.-Q., & Nguyen, L.-T. (2025). Optimizing and restructuring resources for sustainable firm performance in the AI era: the role of dynamic capabilities and circular manufacturing. *Sustainable Futures*, *10*, 101441. https://doi.org/10.1016/j.sftr.2025.101441

Li, Q., & Qin, Y. (2023). AI in medical education: medical student perception, curriculum recommendations and design suggestions. *BMC Medical Education*, *23*(1). https://doi.org/10.1186/s12909-023-04700-8

Lim, W. M., & Ting, D. H. (2012). E-shopping: An analysis of the uses and gratifications theory. *Modern Applied Science*, *6*(5), 48–63. https://doi.org/10.5539/mas.v6n5p48

Loh, X. M., Lee, V. H., Tan, G. W. H., Ooi, K. B., & Dwivedi, Y. K. (2021). Switching from cash to mobile payment: what's the hold-up? *Internet Research*, *31*(1), 376–399. https://doi.org/10.1108/INTR-04-2020-0175

Low, M. P., Cham, T. H., Chang, Y. S., & Lim, X. J. (2023). Advancing on weighted PLS-SEM in examining the trust-based recommendation system in pioneering product promotion effectiveness. *Quality and Quantity*, *57*, 607–636. https://doi.org/10.1007/s11135-021-01147-1

Maican, C. I., Sumedrea, S., Tecau, A., Nichifor, E., Chitu, I. B., Lixandroiu, R., & Bratucu, G. (2023). Factors Influencing the Behavioural Intention to Use AI-Generated Images in Business: A UTAUT2 Perspective With Moderators. *Journal of Organizational and End User Computing*, *35*(1). https://doi.org/10.4018/JOEUC.330019

Martin Fishbein, & Icek Ajzen. (1980). *Understanding Attitudes and Predicting Social Behavior*.

Mehedi Hasan Emon Graduate Student, M., & Hassan Associate Dean, F. (2023). Predicting Adoption Intention of ArtificialIntelligence- A Study on ChatGPT. In *AJSE* (Vol. 22, Number 2).

Mohd Rahim, N. I., A. Iahad, N., Yusof, A. F., & A. Al-Sharafi, M. (2022). AI-Based Chatbots Adoption Model for Higher-Education Institutions: A Hybrid PLS-SEM-Neural Network Modelling Approach. *Sustainability (Switzerland)*, *14*(19). https://doi.org/10.3390/su141912726

Moiinvaziri, M., & Razmjoo, S. A. (2014). Demotivating Factors Affecting Undergraduate Learners of Non-English Majors Studying General English: A Case of Iranian EFL Context. *The Journal of Teaching Language Skills (JTLS)*, *5*(4).

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, *2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192

Nguyen, A.-H. D., Pham, N.-U. T., Lin, P.-T., Dang, T.-Q., Tran, P.-T., Le, T.-T., Phan, T.-T. C., & Nguyen, L.-T. (2024). Acceptance and use of live streaming on metaverse in Vietnam: An analysis with the UTAUT2. *Journal of Infrastructure, Policy and Development*, *8*(8), 6069. https://doi.org/10.24294/jipd.v8i8.6069

Nguyen, L.-T., Phan, T.-T. C., & Dang, T.-Q. (2025). The Power of Interactive Mobile Advertising: How Self-brand Congruity Shapes Brand Engagement in Self-concept. *Journal of Creative Communications*.

https://doi.org/10.1177/09732586251359718

Nur, A., Fatihanisya, S., & Purnamasari, S. D. (2021). Penerapan Model Unified Theory of Acceptence And Use of Technology 2 Terhadap Perilaku Pelanggan e-Commerce Shopee Indonesia Di Kota Palembang. *Journal of Information Systems and Informatics*, *3*(2). http://journal-isi.org/index.php/isi

Phan, L.-G. N., Tri, D. Q., Dang, S.-H., & Nguyen, L.-T. (2025). Hooked on Livestreaming: What Drives Customer Repurchase Intention in E-Commerce? *Journal of Creative Communications*. https://doi.org/10.1177/09732586241311001

PHÙNG VĂN ĐỆ. (2012). *Nghiên cứu thực trạng và đề xuất giải pháp học từ vựng tiếng Anh của sinh viên không chuyên ngành tiếng Anh Trường Đại học Trà Vinh*.

Piarna, R., Fathurohman, F., & Purnawan, N. N. (2020). Understanding online shopping adoption: The unified theory of acceptance and the use of technology with perceived risk in millennial consumers context. *JEMA: Jurnal Ilmiah Bidang Akuntansi Dan Manajemen*, *17*(1), 51. https://doi.org/10.31106/jema.v17i1.5050

Rahiman, H. U., & Kodikal, R. (2024). Revolutionizing education: Artificial intelligence empowered learning in higher education. *Cogent Education*, *11*(1). https://doi.org/10.1080/2331186X.2023.2293431

Romero-Rodríguez, J. M., Ramírez-Montoya, M. S., Buenestado-Fernández, M., & Lara-Lara, F. (2023). Use of ChatGPT at University as a Tool for Complex Thinking: Students' Perceived Usefulness. *Journal of New Approaches in Educational Research*, *12*(2), 323–339. https://doi.org/10.7821/naer.2023.7.1458

Shaping the Future of Learning : The role of AI in Education 4.0 : Insight Report. (2024).

Sledgianowski, D., & Kulviwat, S. (2009). Using social network sites: The effects of playfulness, critical mass and trust in a hedonic context. *Journal of Computer Information Systems*, *49*(4), 74–83. https://doi.org/10.1080/08874417.2009.11645342

Spector, P. E., Rosen, C. C., Richardson, H. A., Williams, L. J., & Johnson, R. E. (2019). A New Perspective on Method Variance: A Measure-Centric Approach. *Journal of Management*, *45*(3), 855–880. https://doi.org/10.1177/0149206316687295

Sucahyo, Y. N., & Ardyan, E. (2022). The Effect of Unified Theory of Acceptance and Ue of Technology (UTAUT) on Behavior Intention and Use Behavior in Buying Baby Product Online. *International Journal of Economics, Business and Management Research*, *06*(11), 89–99. https://doi.org/10.51505/ijebmr.2022.61107

Tan, G. W. H., & Ooi, K. B. (2018). Gender and age: Do they really moderate mobile tourism shopping behavior? *Telematics and Informatics*, *35*(6), 1617–1642. https://doi.org/10.1016/j.tele.2018.04.009

Teo, A. C., Tan, G. W. H., Ooi, K. B., Hew, T. S., & Yew, K. T. (2015). The effects of convenience and speed in m-payment. *Industrial Management and Data Systems*, *115*(2), 311–331. https://doi.org/10.1108/IMDS-08-2014-0231

Tien, P. C. T., Luan, N. T., & Tri, D. Q. (2023). Exploring the brand experience of Korean brands on customer interactions in Ho Chi Minh City, Vietnam: non-linear structural equation modelling approach. In T. Van Tieng (Ed.), *Kỷ yếu hội thảo khoa học quốc tế Việt - Ha\`n 2023* (pp. 276–289). Information and Communications Publishing House; ZBW - Leibniz Information Centre for Economics. https://hdl.handle.net/10419/278122

Tran, T.-T. T., Dang, T.-Q., Nguyen, L.-T., & Dang, D.-V. T. (2025). Blockchain Applications in Value Added Tax Refund: A Deep Learning-Based Dual-Stage SEM-ANN Analysis. *International Journal of Supply and Operations Management*, *12*(3), 293–317. https://doi.org/10.22034/ijsom.2025.110332.3054

van Twillert, A., Kreijns, K., Vermeulen, M., & Evers, A. (2020). Teachers' beliefs to integrate Web 2.0 technology in their pedagogy and their influence on attitude, perceived norms, and perceived behavior control. *International Journal of Educational Research Open*, *1*. https://doi.org/10.1016/j.ijedro.2020.100014

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a Research Agenda on Interventions. In *The Author Journal compilation C* (Vol. 39). Decision Sciences Institute.

Venkatesh, V., Smith, R. H., Morris, M. G., Davis, G. B., Davis, F. D., & Walton, S. M. (n.d.). *Quarterly USER ACCEPTANCE OF INFORMATION TECHNOLOGY: TOWARD A UNIFIED VIEW1*.

Venkatesh, V., Walton, S. M., & Thong, J. Y. L. (2012). *Quarterly Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology1*. http://about.jstor.org/terms

Verplanken, B., Wood, W., Cohen, J., Lind, A., Lynch, J., Quinn, J., & Rodriguez, D. (2006). *Interventions to Break and Create Consumer Habits*. *25*(1), 1547–7207.

Yue, K., Kong, H., & Thong, usthk. (2008). *EXAMINING USER ACCEPTANCE OF SMS: AN EMPIRICAL STUDY IN CHINA AND HONG KONG*. http://www.mii.gov.cn

Zeithaml, V. A., Walker, O. C., Lutz, R., Park, C. W., & Schmalensee, D. (1988). Synthesis of Evidence. In *Journal of Marketing* (Vol. 52).