FACTORS INFLUENCING THE ACCEPTANCE OF USING GENERATIVE AI TO SUPPORT ENGLISH LANGUAGE LEARNING AMONG UNIVERSITY STUDENTS: A CASE STUDY IN VIETNAM

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Abstract - This study investigates factors influencing Vietnamese university students' acceptance of generative AI tools (e.g., ChatGPT, Gemini) in English learning. Using a mixed methods design and based on TAM and UTAUT frameworks, it proposed a model with eight factors affecting students' "Intention to Use AI." Linear regression analysis indicated that these factors explained 34.8% of the variance ($R^2 = 0.348$). "Perceived Usefulness" (PU) had the strongest effect ($\beta = 0.458$, $p < 0.001$), followed by "Perceived Ease of Use" (PEOU, $\beta = 0.116$), "Institutional and Instructor Support" (IIS, $\beta = 0.125$), "Concern about Accuracy" (CAA, $\beta = 0.135$), and "Self-Regulated Learning" (SRL, $\beta = 0.133$). "Social Influence", "Trust in AI", and "Attitude" were not significant ($p > 0.05$). The study highlights the importance of institutional AI policies and recommends fostering students' critical thinking to prevent over-reliance on AI.

Key words - Generative AI; English Language Learning; Technology Acceptance; Perceived Usefulness; Self-Regulated Learning

1. Introduction

Artificial intelligence (AI) is increasingly developing rapidly in education, creating many new opportunities for language learning. According to Wang et al. [1], AI systems in education (AIED – AI in Education) have demonstrated the ability to enhance students' exam results by up to 62% through adaptive learning, while the use of AI in general helps improve student learning performance [1]. The application of generative AI, such as chatbots, pronunciation feedback tools, and grammar correction software, is being widely researched and implemented to personalize the language learning process. In a systematic review analyzing 125 studies from 2013 to 2023, Zhu & Wang pointed out that writing and speaking are the productive skills most supported by AI in language learning, through technologies such as automated writing evaluation systems, speech recognition, machine translation, and interactive bots [2].

Tools such as ChatGPT, Gemini, DeepSheep, and Copilot have been commonly used by students to support translation, pronunciation practice, essay writing, communication, and homework. From a global perspective, Zhai et al. [3] examined the phenomenon of excessive dependence on AI dialogue systems in an international context, revealing that the trust and immediate utility of AI-generated outcomes prompt students to utilize them with limited verification, consequently impairing their critical thinking and information analysis skills [3]. In addition, based on the TAM model, Musyaffi et al. [4] indicates that students perceive AI technology as relatively easy to use and supportive of learning; however, risk and reliability remain key factors hindering its widespread adoption.

In Vietnam, the acceptance of AI in foreign language education still faces many challenges. A study by Cung et al. [5] mentions that Vietnamese university students perceive AI tools as beneficial for enhancing writing quality, productivity, and engagement. However, they also express concerns about overdependence and the potential impact on personal creativity. Similarly, research by N. T. Xuyen [6], which surveyed English majors at universities in Ho Chi Minh City, found that students had used various AI tools in learning English and generally hold a positive attitude toward using AI tools in their English learning. Nevertheless, they also voice concerns that such tools may hinder the development of their critical thinking and problem-solving abilities [6].

Although the application of AI in language learning has become increasingly popular, current research evidence indicates that there is still a significant gap in assessing the level of foreign language students' acceptance of AI tools. Many students are familiar with using tools such as ChatGPT, Gemini, Copilot, or DeepSeek to assist with essay writing, pronunciation practice, translation, or communication exercises; however, the number of quantitative studies, especially in Vietnam, aimed at identifying and measuring factors that promote or hinder this acceptance remains limited [7]. Existing studies mainly focus on describing the phenomenon or conducting preliminary surveys and have not yet developed a comprehensive analytical framework for students' acceptance of AI technology in language learning.

This research gap raises an urgent question regarding the factors influencing students' decisions to use AI in learning English. Widely adopted theoretical frameworks of technology acceptance, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), propose that acceptance behavior is influenced by variables such as perceived usefulness (PU), perceived ease of use (PEOU), social influence (SI), facilitating conditions, and trust in the tool [8]; [9]. In the Vietnamese context, these variables may interact with specific factors such as learning culture, infrastructure, school policies, and learners' technological competence. Therefore, identifying the specific factors that influence foreign language students' decisions to use AI in English learning not only addresses existing research gaps but also offers a practical foundation for education managers, lecturers, and AI tool developers.

Based on the research context and issues presented, this study has three main objectives. First, it aims to identify the factors influencing the acceptance and use of AI tools - specifically ChatGPT, Gemini, DeepSeek, and Copilot - in English language learning among university students majoring in foreign languages. Identifying these factors not only helps establish an appropriate analytical framework but also provides a practical basis for evaluating technology acceptance in the field of language learning. Second, the study examines the extent to which each factor influences the intention to use, thereby determining the most important factors shaping learners' attitudes and behaviors. Third, drawing on empirical findings, it proposes feasible solutions to enhance both the acceptance and effective application of AI tools in foreign language learning in Vietnam.

2. Theoretical framework and research model

2.1. Theoretical Framework

To develop a research model on the factors influencing the acceptance of ChatGPT, Gemini, DeepSeek and Copilot in English learning, three theoretical frameworks are employed: TAM, UTAUT, and the Theory of AI-Assisted Learning. The first is TAM, proposed by Davis [10], which posits that technology acceptance is primarily shaped by two cognitive factors: PU and PEOU. When learners perceive a tool as both beneficial for improving learning efficiency and easy to use, they are more likely to develop a positive attitude toward it and, consequently, a stronger intention to adopt it [10]. In the context of the increasing prevalence of foreign languages, the rising emphasis on language learning helps explain why students choose to adopt or reject AI tools for English learning.

The second framework is UTAUT, developed by Venkatesh et al. [11]. UTAUT extends TAM by incorporating additional variables, such as SI and facilitating conditions. According to this model, technology acceptance is shaped not only by individual perceptions but also by encouragement from peers, instructors, and institutions, as well as by access to devices, infrastructure, and technical support [11]. In the Vietnamese educational context, where SI and organizational support may exert stronger effects than in more developed settings, UTAUT offers a more comprehensive framework for analyzing students' acceptance of AI tools.

Thirdly, research referencing the AI-Assisted Learning Theory highlights the role of AI in personalizing the learning experience and offering timely feedback to users. According to this theory, AI can act as a learning assistant, supporting learners according to their individual needs and learning levels, thereby boosting motivation, engagement, and learning effectiveness. Within English language learning context, AI can recommend appropriate materials, correct grammatical errors, provide pronunciation feedback, simulate conversations, and assist in content creation, contributing to the comprehensive development of students' skills. Applying this theory helps supplement the learning value aspect alongside technology acceptance. Hence, this helps building a research model that is both comprehensive and suitable for the practical application of AI in foreign language education in Vietnam.

2.2. Proposed influencing factors

PU is referred to as the degree to which a user believes that using a system enhances their work or learning performance [10]. In the context of language learning with AI, PU reflects students' evaluations that tools such as ChatGPT, Gemini, or Copilot help them write more effectively, speak more fluently, correct errors more quickly, and improve the overall quality of English learning.

PEOU refers to the extent to which users believe that using technology will be free of difficulty, require minimal effort, and be easy to learn and operate. Regarding TAM, PEOU affects PU and the attitude towards usage, which in turn indirectly influences the intention to use. In studies on AI in education, PEOU is often found to be positively correlated with the intention to use.

SI in UTAUT is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (p. 451) [11]. In other words, this construct can involve the influence of instructors, peers, friends, or family members on students' decisions to adopt new technologies such as AI applications.

Institutional and Instructor Support (IIS) includes providing resources (computers, AI software), training, guidance on usage, encouragement, incentive policies, and an organizational culture that supports technological innovation. This factor is closely correlated with facilitating conditions in UTAUT. According to Velli and Zafiropoulos [12] in their investigation of factors influencing the acceptance of educational AI tools, institutional and lecturer support serves as a critical determinant in reducing users' anxiety and enhancing their capability to adopt AI tools.

Trust in AI Technology (TAI) refers to users' confidence in the reliability, accuracy, and fairness of AI systems. one of the major challenges language learners encounter when adopting AI technologies is the concern that AI-generated feedback and content may lack accuracy or contain errors. Such issues can undermine users' trust in technology, weaken their positive attitudes, and consequently diminish their intention to use it. Consistent with this, Nazaretsky et al. [13] identified perceived accuracy as a key predictor of users' trust and acceptance of AI-powered educational tools.

Delcker's study [14], which surveyed first-year university students, revealed that learners who perceive themselves as lacking the knowledge and skills to assess or verify the accuracy of AI-generated outputs are less likely to intend to use AI tools for practical learning purposes. Drawing on these findings, the present research model identifies **Concerns about Accuracy (CAA)** as a variable that negatively influences both attitude and behavioral intention toward using AI tools. Based on these results, in the proposed research model, CAA is identified as a variable that negatively affects attitude and behavioral intention. Concerns about the accuracy of AI (CAA) negatively affect university students' intention to use AI for learning English.

As reported by Cho and Seo [15] in their study examining the dual mediating effects of anxiety and acceptance attitude on the relationship between perceptions of and intentions to use AI technology, nursing students in South Korea were surveyed. The results showed that acceptance attitude is strongly and positively correlated with the intention to use AI, and this attitude also serves as an important bridge between AI perception and intention to use, while being negatively influenced by AI-related anxiety [15]. From these studies, it can be concluded that in the proposed model, **AI in education (ATT)** should be considered an independent variable affecting the intention to use. It is suggested that Attitude toward using AI in education (ATT) has a direct impact on university students' intention to use AI for learning English.

Self-Regulated Learning (SRL) is the ability of learners to set their own goals, monitor their learning progress, adjust strategies, and evaluate their own learning outcomes. In an AI-supported environment, SRL is particularly important because AI tools often offer multiple options, requiring learners to actively choose, control, and use them effectively. Many studies have shown that learners with high SRL tend to have better attitudes and higher learning performance when using new technologies, as they know how to self-regulate and leverage supportive features.

2.3. Proposed Research Model

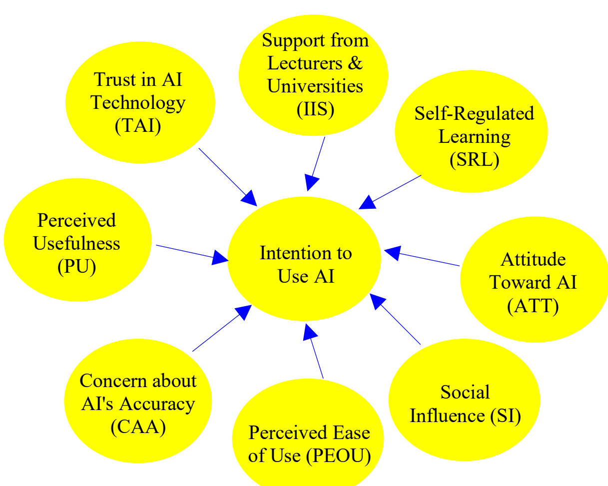

Figure 1. *Proposed model*

Based on the theoretical foundations of TAM, UTAUT, and previous studies, this research develops a model to analyze the factors influencing students' intention to accept and use AI in learning English. Specifically, the model focuses on eight factors: PU, PEOU, SI, support from lecturers and the university (IIS), concern about AI accuracy (CAA), TAI, attitude toward AI (ATT), and students' SRL ability (SRL). The research model is illustrated in Figure 1, where the eight independent factors serve as predictor variables while the intention to use AI is the dependent variable. Through this model, the study aims to test and compare the impact levels of each factor, thereby identifying key elements that either promote or constrain the acceptance of AI in foreign language learning.

3. Research methodology

3.1. Research Methodology

To ensure that this study both deeply explores the influencing factors and tests the theoretical model, the authors adopted a mixed-methods approach. Specifically, the research combines quantitative surveys with qualitative analysis to supplement, compare, and reinforce the findings. First, a questionnaire based on the variables in the research model (PU, PEOU, SI, IIS, CAA, TAI, ATT, SRL, and intention to use AI) was constructed using a 5-point Likert scale. This questionnaire will be distributed to a sufficiently large sample of university students studying foreign languages in Vietnam to conduct structural analysis (SEM or PLS-SEM). After data collection, reliability indices (Cronbach's Alpha) and convergent/discriminant validity values will be tested to assess the validity of the model.

Next, to gain a better understanding of the underlying causes and to clarify the quantitative results, the study will conduct in-depth interviews with a small group of students and faculty members. Semi-structured interviews are designed to explore experiences, perspectives, as well as barriers or motivations that may not be clearly reflected in the survey. Qualitative data will be coded and analyzed using thematic analysis to extract themes related to perceptions of usefulness, ease of use, trust, CAA, support from the institution, and self-learning ability.

The simultaneous implementation of these two methods allows for triangulation between quantitative and qualitative data, thereby enhancing the reliability, generalizability, and practical value of the results. This mixed-methods approach has been recommended in recent international studies, such as the research conducted by Li et al. [16] on Chinese students' perceptions of AI, and that by Hanshaw and Sullivan [17] examining barriers to the adoption of AI course assistants. These studies demonstrate that the mixed-methods approach not only helps test theoretical models but also provides qualitative context to interpret statistical results, thereby supporting the formulation of policy and practice recommendations that are better suited to the Vietnamese educational context.

3.2. Participants and Scope of the Study

The research participants of this study are students currently studying at universities specializing in foreign languages in Vietnam. This is a group with a high demand for using AI tools to support learning English, such as translation, pronunciation practice, academic writing, communication, or completing assignments. Choosing foreign language students allows the study to focus on learners who have motivation, a need, and frequent exposure to AI tools for language learning, thereby more clearly reflecting the factors influencing the acceptance and intention to use these tools.

The scope of the study focuses on a single training institution to ensure feasibility and depth of data. Specifically, the research selects a major foreign language training institution in Vietnam, such as the University of Foreign Languages – University of Da Nang. This is one of the institutions with a large student body, a tradition of foreign language teaching, and has begun implementing technology-integrated methods, including AI, to support learning. This scope allows the study to collect data that is suitable for the real context while also enabling comparisons between schools to enhance the generalizability of the results.

3.3. Data Collection Instruments

The survey questionnaire was developed based on the variables in the research model (PU, PEOU, SI, IIS, CAA, TAI, ATT, SRL, and intention to use AI). Each factor was measured using standardized scales from previous studies, adjusted to fit the context of language learning in Vietnam. The questions were designed with a 5-point Likert scale (from 1 – Strongly Disagree to 5 – Strongly Agree) to reflect the respondents' level of agreement. This tool enables the collection of quantitative data from a large student sample, providing a basis for statistical analysis and hypothesis testing.

Interviews were conducted with a group of students and lecturers selected from universities specializing in foreign languages. The interviews focused on exploring practical experiences, personal perspectives, difficulties, advantages, and other factors related to the use of AI tools in language learning. The data collected from the interviews will complement, explain, and clarify the quantitative results from the questionnaires, while also helping to identify new factors not included in the model.

The simultaneous use of both tools aims to ensure the completeness, reliability, and value of the data, while also facilitating the comparison between quantitative and qualitative results to draw conclusions and make recommendations suitable for the context of Vietnamese education.

3.4. Data Analysis Methods

The data collected from the questionnaire responses of language major students will be filtered to remove any non-standard data, encoded, and entered into SPSS software for further analysis. First, the reliability of the data will be checked using Cronbach's Alpha coefficient. As stated by Nunnally and Bernstein [18], Cronbach's Alpha value between 0.7 and 0.9 is regarded as acceptable.

Next, an exploratory factor analysis (EFA) will be conducted to identify the structure of the latent factors of the scale. The KMO values and Bartlett's test will be used to determine whether the factor structure is acceptable and statistically significant. For the KMO coefficient, a KMO value ≥ 0.5 is acceptable, and a KMO ≥ 0.8 is ideal for use in subsequent analyses [19]. For Bartlett's test, a p-value < 0.05 indicates that the observed variables are sufficiently correlated with each other [20]. To understand the latent structure of the data, the rotated factor matrix will indicate whether the loadings of the observed variables are strong enough for further analysis. Factor loadings ≥ 0.5 are considered statistically significant [19]. If this criterion is not met, adjustments or variable removal will be performed to achieve a structure that fits the data.

After the scales were validated, the study used multiple linear regression analysis to examine the influence of independent factors (PU, PEOU, SI, IIS, CAA, TAI, ATT, SRL) on the intention to use AI in learning English. Standardized regression coefficients (Beta) and p-values were used to determine the impact of each factor on the intention to use AI. Multiple regression analysis also helped test the research hypotheses and compare the magnitude of different factors, thereby providing appropriate recommendations.

4. Findings

4.1. Reliability Testing

Table 1. *Reliability statistics of the factors*

Factors	Cronbach's Alpha
PU	0.864
PEOU	0.822
SI	0.874
IIS	0.891
CAA	0.901
TAI	0.902
ATT	0.869
SRL	0.866
Intention to use AI (INT)	0.834

The reliability statistics presented in Table 1 shows that all scales achieved high values, ranging from 0.822 to 0.902. A Cronbach's Alpha coefficient ≥ 0.70 is considered acceptable for research in the social sciences, and ≥ 0.80 indicates that the scale has good reliability [18]. Thus, the scales in this study all have very high reliability, ensuring stability and internal consistency among the observed variables within the same factor.

The factors CAA, TAI, and IIS have the highest Cronbach's Alpha coefficients (above 0.89–0.90), indicating that the observed variables within each of these factors are highly consistent and effectively measure the concepts they represent. The remaining factors, such as PU, PEOU, SI, ATT, and SRL, all have Cronbach's Alpha coefficients >0.82, also exceeding the recommended threshold and reflecting good reliability.

Specifically, the INT scale achieved Cronbach's Alpha of 0.834, indicating sufficient stability and reliability for use in exploratory factor analysis (EFA) and subsequent linear regression. This allows the conclusion that the entire measurement system of the study meets standards and can be used for the next steps of analysis to test the theoretical model and the proposed hypotheses.

4.2. Exploratory Factor Analysis

Table 2. *KMO values and Bartlett's test*

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.771
Bartlett's Test of Sphericity	Approx. Chi-Square	5100.548
	df	666
	Sig.	.000

As shown in Table 2, the KMO coefficient = 0.771, higher than the minimum threshold of 0.5, indicating that the data are quite suitable for conducting exploratory factor analysis (EFA). This value falls within the 0.7–0.8 range, considered "fair," meaning that the correlation matrix among the variables is sufficiently strong to extract latent factors. The Bartlett test has a significant level of Sig. = 0.000 < 0.05. This demonstrates that the variables are significantly correlated with each other, making them suitable for factor analysis. Thus, both the KMO and Bartlett's Test indices confirm that the data collected in the study meet the necessary conditions for performing exploratory factor analysis (EFA) to identify the latent structure of the scales.

Table 3. *Factor rotation matrix table*

Rotated Component Matrix[a]

	Component								
	1	2	3	4	5	6	7	8	9
PU5	.878								
PU1	.813								
PU4	.790								
PU2	.789								
PU3	.778								
CAA5		.890							
CAA4		.861							
CAA1		.806							
CAA2		.737							
CAA3		.713							
IIS1			.894						
IIS2			.862						
IIS4			.856						
IIS3			.843						
INT1				.800					
INT4				.775					
INT5				.714					
INT2				.685					
INT3				.675					
SRL2					.909				
SRL3					.853				
SRL1					.827				
SRL4					.773				
ATT4						.867			
ATT2						.850			
ATT1						.838			
ATT3						.818			
PEOU4							.871		
PEOU1							.841		
PEOU3							.775		
PEOU2							.726		
TAI1								.915	
TAI2								.910	
TAI3								.898	
SI3									.910
SI1									.877
SI2									.870

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 6 iterations.

Table 3 shows that the factor rotation matrix table, it can be seen that the data were rotated into 9 factors, which corresponds well with the 8 predetermined factors and the students' intention to use. All observed variables have high factor loadings and converge correctly on the theoretical factors, indicating that the scale has good convergent validity. Specifically, the CAA group has factor loadings ranging from 0.778 to 0.878; the PU group from 0.713 to 0.890; the IIS group from 0.843 to 0.894; the INT group from 0.675 to 0.800; the SRL group from 0.773 to 0.909; the ATT group from 0.818 to 0.867; the PEOU group from 0.726 to 0.871; the TAI group from 0.898 to 0.915; and the SI group from 0.870 to 0.910.

All of these values far exceed the recommended threshold of 0.50 and reach a good level above 0.70 according to Hair et al. [19], showing that the observed variables well represent the latent concept and exhibit high convergence. At the same time, there is no significant cross-loading between the factors, reflecting a clear discriminant validity among the measurement structures. Therefore, the factors in the model are confirmed to have a stable and reliable structure.

This result confirms that the constructed research model has high validity and can be used for subsequent analysis steps such as confirmatory factor analysis or structural equation modeling to test the relationships between factors. This is an important basis to ensure the reliability and accuracy of the research results.

4.3. Multiple Linear Regression Analysis

Table 4. *Model Summary Table*

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.590[a]	.348	.326	.66459	.348	16.012	8	240	.000	1.681

a. Predictors: (Constant), F_SRL, F_SI, F_IIS, F_TAI, F_PEOU, F_ATT, F_PU, F_CAA

b. Dependent Variable: F_INT

Table 4 shows a correlation coefficient R = 0.590, indicating a strong relationship between the independent variables (PU, PEOU, SI, IIS, TAI, CAA, ATT, SRL) and the dependent variable (intention to use AI – INT). The R Square value of 0.348 indicates that the 8 factors in the model explain 34.8% of the variance in the intention to use AI. When adjusted for the number of variables (Adjusted R Square = 0.326), the model still maintains a fairly stable level of explanation, reflecting a significant fit between the data and the theoretical model.

The standard deviation of the estimation error is 0.66459, indicating a moderate level of dispersion. With a significance level of 0.000 < 0.001, it confirms that the overall regression model is highly statistically significant. The Durbin–Watson coefficient = 1.681 falls within the acceptable range (1.5–2.5), indicating that there is no serious autocorrelation of residuals. This enhances the reliability of the regression analysis results.

Overall, the model has a fairly good explanatory level and meets the suitability requirements, making it usable to examine in detail the influence of each factor on the intention to use AI in learning English, while also serving as a basis for proposing solutions to enhance the acceptance of AI technology in education.

Table 5. *ANOVA Results*

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	56.578	8	7.072	16.012	.000[b]
	Residual	106.002	240	.442		
	Total	162.581	248			

a. Dependent Variable: F_INT

b. Predictors: (Constant), F_SRL, F_SI, F_IIS, F_TAI, F_PEOU, F_ATT, F_PU, F_CAA

The ANOVA in Table 5 for the regression model shows that the total variance of the dependent variable 'Intention to Use AI' (INT) is divided into two parts: variance explained by the model (Regression) and unexplained variance (Residual). Specifically, the total variance is 162.581, of which 56.578 (approximately 34.8%) is explained by the eight independent variables in the model (PU, PEOU, SI, IIS, CAA, TAI, ATT, SRL). The Mean Square value for the Regression part is 7.072, which is significantly higher than the Mean Square of the Residual (0.442), indicating that the model has good explanatory power. In particular, with a significance level of Sig. < 0.001, it confirms that the overall linear regression model is statistically highly significant.

This result confirms that the proposed research model is suitable and robust enough to proceed with a detailed analysis of the impact level of each factor. Consequently, the results of subsequent hypothesis testing will have a reliable basis to determine which factor most strongly influences students' intention to use AI in learning English.

The regression results show that the factor with the strongest impact on the intention to use (F_INT) is 'PU' (F_PU), with a Beta coefficient of 0.458 and a statistical significance level of Sig. < 0.001. This indicates that the more clearly students perceive AI as useful for learning or work, the higher their intention to use it. In addition, the factors ' PEOU ' (F_PEOU), 'Support from instructors/school' (F_IIS), 'CAA' (F_CAA), and 'Self-directed learning ability' (F_SRL) all have positive Beta coefficients and Sig. < 0.05, showing that they also have a significant and positive impact on students' intention to use AI. This reflects that besides usefulness, factors such as ease of use, support from the learning environment, students' ability for self-directed learning, and trust in AI accuracy also increase the intention to use AI.

Table 1. *Table Coefficients*

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.629	.614		1.025	.306
	F_PU	.458	.043	.566	10.634	.000
	F_PEOU	.116	.057	.107	2.028	.044
	F_SI	-.075	.051	-.079	-1.491	.137
	F_IIS	.125	.063	.105	1.992	.047
	F_CAA	.135	.065	.111	2.095	.037
	F_TAI	-.002	.045	-.003	-.052	.959
	F_ATT	-.065	.050	-.069	-1.312	.191
	F_SRL	.133	.062	.112	2.137	.034

a. Dependent Variable: F_INT

Conversely, as illustrated in Table 6, the factors “SI” (F_SI), “Trust in AI” (F_TAI), and “Attitude toward AI” (F_ATT) have Sig. values > 0.05 and are therefore not statistically significant. This implies that, in the context of this study, social factors or general trust are not strong enough to influence usage intention. Thus, to enhance students' intention to use AI, it is necessary to focus on improving usefulness, ease of use, accuracy, and providing an appropriate supportive environment rather than relying solely on social factors or general attitudes. From this, the regression equation of the model can be derived as follows:

$$F\_INT = 0.629 + 0.458*F\_PU + 0.116 * F\_PEOU + 0.125 * F\_IIS + 0.135 * CAA + 0.133 * F\_SRL + \varepsilon$$

5. Conclusion and recommendation

5.1. Conclusion

The research results have provided important empirical evidence on the factors influencing the intention to use AI in the learning of students majoring in foreign languages in Vietnam. Linear regression analysis indicates that factors such as PU (F_PU), PEOU (F_PEOU), support from lecturers and the school (F_IIS), concerns about AI accuracy (F_CAA), and students' SRL ability (F_SRL) all have a positive and statistically significant impact on the intention to use AI (F_INT). This suggests that the theoretical model developed is consistent with the actual survey data and accurately reflects the current trends in AI adoption among foreign language students.

First, the results have affirmed the importance of PU and PEOU in the acceptance of AI technology in language learning. When students feel that AI technology provides practical benefits, supports improved learning efficiency, and is easy to access and operate, they are more likely to use it. This aligns with technology acceptance models such as TAM and highlights these two factors as key prerequisites determining technology usage behavior.

Second, support from lecturers and the school plays a strong catalytic role in encouraging students to use AI. Supportive policies, technological infrastructure, and training programs from the school help students not only access technology easily but also use it appropriately and more effectively. This support also helps alleviate students' concerns about the accuracy of AI - a factor that is considered a psychological barrier in the adoption of new technology.

In addition, the results also emphasize the role of students' self-learning abilities and critical thinking in the process of using AI. When learners have good self-learning skills, they will harness AI proactively and creatively, avoiding excessive dependence, thereby maximizing the benefits that technology provides. This shows that the acceptance of AI not only depends on the technology itself but also greatly depends on the individual competence of the learners.

Overall, this study has provided a clear picture of the factors influencing the acceptance of AI in foreign language education. The results emphasize the need for a comprehensive approach, combining the improvement of AI technology quality and reliability, enhancing the supportive and guiding role of instructors, and developing students' self-learning capabilities. This will help promote the sustainable, effective, and responsible use of AI, thereby improving the quality of foreign language training in the current context of digital transformation in education.

5.2. Recommendations

5.2.1. Implications for Universities

Universities specializing in foreign languages should develop and implement clear policies supporting the use of AI in learning. Specifically, schools need to create a "comprehensive AI policy" for teaching, assessment, and learning, including guidelines to ensure transparency, data security, privacy, and ethics when students use AI. As highlighted by Chan [21], implementing a university-wide AI policy across teaching, administration, and operations encourages more effective AI integration [21].

In addition, the school needs to invest in technical infrastructure – stable Internet, sufficiently powerful hardware/computers, access rights to the AI software being used – to avoid creating barriers for students in terms of usage conditions. At the same time, there should be training programs for school leaders and staff – especially lecturers – so that they clearly understand how AI works, its limitations and risks, and how to distinguish incorrect or erroneous content generated by AI.

Finally, schools should provide official guidance or workshops on developing AI skills for students so that they can use AI correctly and scientifically – not just to complete tasks quickly, but to learn better. This policy should encourage students to compare AI feedback with feedback from instructors to enhance their ability to discern accuracy and critically evaluate it. The study by Henderson and colleagues [22] indicates that students consider teacher feedback more trustworthy than AI-generated feedback and value academically oriented feedback more highly [22].

5.2.2. Implications for Lecturers

Instructors need to proactively take on the role of guiding students to use AI effectively and in a balanced manner. First, instructors should design lessons, exercises, and learning activities in which AI serves a supportive role – providing feedback, assisting with writing, and correcting grammar – but does not replace the students' own thinking; there should be tasks that require students to critically reflect and analyze on their own. As indicated by Henderson et al. [22] has shown that although AI feedback is beneficial, students still value teacher feedback more highly for reliability and academic quality [22].

In addition, instructors should use a feedback method that combines AI and instructor feedback, allowing students to compare, evaluate, and learn from both sources. Feedback from instructors can clarify context, assess emotions, and provide creative aspects that AI sometimes miss. It has been found that feedback quality remains a key determinant of students' perceptions of usefulness [23]. In other words, teacher or expert feedback is consistently rated higher than other sources in terms of error explanation, language quality, and responsiveness to content, underscoring the enduring value of human expertise in educational feedback processes.

5.2.3. Implications for Students

Students need to develop independent learning skills and critical thinking to use AI thoughtfully and effectively. Specifically, students should be encouraged to verify and compare information generated by AI with reliable sources, and to question the accuracy, context, and ethics of its use. According to Zhai et al. [3], over-reliance on AI dialogue systems poses a potential threat to learners' cognitive growth. This approach helps balance the convenience benefits of AI with the development of thinking skills.

Finally, students should proactively enhance their knowledge of AI to understand how AI models operate, their limitations, and risks such as data errors and security issues. When students are aware of these issues, they will rely less on AI and use it in a more controlled manner. Agaoglu et al. [24] illustrated that digital literacy plays both mediating and moderating roles in the relationship between AI usage and students' creative thinking abilities. Their research findings suggest that higher levels of digital literacy can develop the positive effects of AI use on creative thinking, while limited digital literacy may weaken this relationship, highlighting the importance of developing digital competencies in educational contexts.

5.3. Future Research Directions

An important future research direction is to expand studies across multiple universities. Currently, many studies on AI acceptance in foreign language learning focus on one or a few universities, sometimes only within the same province/city, making it difficult to generalize the differences in organizational culture, technical infrastructure, and learning environment. Conducting surveys among foreign language specialized universities located in different regions (North, Central, South), as well as between public and private institutions, will help clarify the contextual influences on variables such as support conditions, SI, and technological proficiency. As an illustration, Mohamed et al. [25] surveyed students from Egypt, Saudi Arabia, Spain, and Poland and found that levels of intrinsic motivation and learning experience varied according to nationality and field of study. Applying this survey model in the context of multiple schools in Vietnam would also help identify differences by region, type of school, and education level, facilitating the proposal of appropriate support policies.

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