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Modeling pre-service efl teachers' attitudes toward Artificial Intelligence in language education

Arezoo Ashoori Tootkaboni, Mojtaba Maghsoudi

Department of English Language Teaching, Farhangian University, Tehran, Iran

Abstract

Although there has been a lot of interest in the use of artificial intelligence (AI) in language instruction, yet research on pre-service English as a Foreign Language teachers' (PSEFLTs) attitude toward AI remains limited. This study investigates the key determinants influencing PSEFLTs' attitudes toward AI integration in language education, focusing on perceived usefulness, perceived ease of use, AI confidence, perceived benefits of AI in teaching, and subjective norms. Utilizing a structural equation modeling (SEM) approach, data were collected from 128 PSEFLTs across three teacher education universities in Iran. The findings reveal that perceived usefulness, perceived ease of use, subjective norms, and perceived benefits of AI in teaching significantly shape PSEFLTs' attitudes toward AI, while AI confidence did not have a statistically significant effect. These findings highlight how crucial it is to implement focused teacher training programs in order to improve future educators' confidence and proficiency with AI integration. With its practical recommendations for policymakers and teacher educators in creating AI-focused curricula that meet pedagogical objectives, the study adds to the continuing conversation on AI in education.

Key words

Artificial intelligence; language education; teacher education; technology integration.

Contacto:
Arezoo Ashoori Tootkaboni - a.ashoori1985@gmail.com

Modelado de las actitudes de los futuros profesores de inglés como lengua extranjera hacia la inteligencia artificial en la enseñanza de idiomas

Resumen

Aunque ha habido un gran interés en el uso de la inteligencia artificial (IA) en la enseñanza de idiomas, la investigación sobre la actitud de los futuros profesores de inglés como lengua extranjera (PSEFLT, por sus siglas en inglés) hacia la IA sigue siendo limitada. Este estudio investiga los determinantes clave que influyen en las actitudes de los PSEFLT hacia la integración de la IA en la educación de idiomas, centrándose en la utilidad percibida, la facilidad de uso percibida, la confianza en la IA, los beneficios percibidos de la IA en la enseñanza y las normas subjetivas. Utilizando un enfoque de modelo de ecuaciones estructurales (SEM), se recopilaron datos de 128 PSEFLT de tres universidades de formación docente en Irán. Los hallazgos revelan que la utilidad percibida, la facilidad de uso percibida, las normas subjetivas y los beneficios percibidos de la IA en la enseñanza moldean significativamente las actitudes de los PSEFLT hacia la IA, mientras que la confianza en la IA no tuvo un efecto estadísticamente significativo. Estos resultados subrayan la importancia de implementar programas de formación docente específicos para mejorar la confianza y la competencia de los futuros educadores en la integración de la IA. Con sus recomendaciones prácticas para los responsables de políticas y los formadores de docentes en la creación de planes de estudio centrados en la IA que cumplan con los objetivos pedagógicos, el estudio contribuye a la conversación continua sobre la IA en la educación.

Palabras clave

Inteligencia artificial; educación de idiomas; formación docente; integración de tecnología.

Introduction

Artificial intelligence (AI) has emerged as a transformative force in education, reshaping teaching strategies through advanced tools that enhance teaching and learning outcomes. Its potential is increasingly recognized for diverse applications, including facilitating meaningful interactions, personalized learning, and interactive assessments (Hopcan et al., 2023; Zhang & Aslan, 2023). AI equips teachers with resources to strengthen lesson planning, professional development, assessment, and the creation of customized content (Kasneci et al., 2023). Moreover, AI tools improve learners' achievements and experiences (Kasneci et al., 2023), while offering individualized opportunities (Rane et al., 2024).

Language education has seen growing research on students' and teachers' attitudes toward AI integration. Studies emphasize AI's potential to improve outcomes, streamline teaching, and enable individualized instruction (Kasneci et al., 2023). Research also highlights educators' perspectives on benefits and challenges, particularly regarding professional growth, technological readiness, and academic integrity (Dimitriadou & Lanitis, 2023).

Despite this interest, research on pre-service English as a Foreign Language teachers' (PSEFLTs) attitude remains scarce. While in-service teachers and students have been widely studied, less focus has been given to pre-service teachers, who represent the future of language education. Their attitudes are critical, as they shape willingness and intention to adopt AI, influencing education's trajectory. Existing research often emphasizes technological affordances and outcomes but overlooks psychological and pedagogical factors. Although variables such as AI confidence, perceived usefulness, and subjective norms have been examined elsewhere, their impact on PSEFLTs is underexplored.

This study addresses these gaps by investigating determinants of PSEFLTs' attitudes, including perceived usefulness (PU), perceived ease of use (PEU), subjective norms (SN), AI confidence (AIC), and perceived benefits of AI in teaching (PBAIT). Employing a SEM approach, it offers empirical insights for teacher education programs and policymakers developing AI-oriented curricula.

Literature review

AI in language education

Recent advancements in AI have spurred numerous studies on its integration into language instruction (e.g., Fathi et al., 2024; Har, 2023; Liu et al., 2023; Liu & Ma, 2024; Marzuki et al., 2023). These works emphasize AI's potential to transform language teaching by enhancing learners' skills and enriching instructional practices. AI-assisted tools, valued for improving proficiency and creating engaging learning experiences, have received growing attention (e.g., Jeon & Lee, 2023; Xu & Ouyang, 2022). For example, Hsu et al. (2023) showed that EFL students using AI tools outperformed peers in vocabulary proficiency, while Song and Song (2023) found improvements in students' motivation and writing skills.

AI has also proven effective in advancing speaking abilities through speech recognition and interactive dialog bots. Studies demonstrate that AI-assisted devices enhance speaking proficiency (Fathi et al., 2024; Junaidi, 2020; Zou et al., 2023). Acting as conversational partners, AI tools provide authentic exchanges and personalized environments (Jeon, 2024; Tai & Chen, 2024).

Beyond skill development, research highlights AI's psychological and pedagogical benefits. It provides immediate feedback and supportive contexts (El Shazly, 2021; Hapsari & Wu, 2022), reduces anxiety through personalization and self-study (Hawanti & Zubaydulloevna, 2023; Xiao et al., 2024), and fosters motivation, self-esteem, and enjoyment (Xiao et al., 2024). Collectively, these findings indicate AI enhances language competency while cultivating positive attitudes toward language acquisition.

Theoretical framework

The Theory of Planned Behavior (TPB), introduced by Ajzen in the late 1980s (Ajzen, 1991), provides a valuable framework for examining human behavior in education, learning, and technology adoption (Knauder & Koschmieder, 2019). TPB posits that behavior is shaped by attitudes, subjective norms (SN), perceived ease of use (PEU), and perceived usefulness (PU), which collectively influence behavioral intentions and, ultimately, actions. Attitudes, reflecting individuals' evaluative judgments of behaviors, are central to this model. In teaching and learning, positive attitudes, shaped by favorable perceptions of instructional outcomes, encourage intentions and active engagement. SN, in turn, highlights the impact of societal and peer expectations on behavior (Conner & Armitage, 1998). Approval from colleagues, administrators, and the academic community acts as a strong motivational force, encouraging alignment with educational norms.

The flexibility of TPB is demonstrated in its application across education, including studies on massive open online courses (Wang et al., 2024) and mobile learning (Cheon et al., 2012). It has also been used to explore student-centered strategies such as peer learning and technology integration (Sadaf & Johnson, 2017). In educational psychology, TPB supports research on teachers' adoption of assessment methods, classroom management, and evidence-based practices (Knauder & Koschmieder, 2019).

By analyzing the interplay among attitudes, norms, and perceived control, TPB offers a comprehensive framework for understanding educational decision-making and guiding interventions, including the integration of generative AI in teaching and learning.

Hypotheses development

Building upon the TPB framework, this study examines a number of important variables that influence pre-service teachers' attitudes toward AI, including PU, PEU, SN, confidence, and PBAIT.

Perceived usefulness and perceived ease of use (PU & PEU). PU, derived from the Technology Acceptance Model (TAM) (Davis, 1989), is the degree to which teachers believe AI enhances teaching effectiveness. Research suggests that when teachers perceive AI as an effective instrument that improves instructional quality and student involvement, they are more likely to adopt it (Wang et al., 2024). PEU, another key construct from TAM, relates to how effortlessly teachers believe AI can be implemented in their teaching practice. If AI tools are seen as user-friendly and require minimal effort to learn, teachers are more inclined to embrace them (Ayanwale et al., 2022). The findings of Maheshvari (2024), Ma and Lei (2024), Sanusi et al. (2023), and Zhang et al. (2023) further supported the notion that PU and PEU are important factors in impacting the behavioral intention of AI adoption. Considering the aforementioned, we postulated that:

H1. PU plays a positively significant influence on the attitude of PSEFLTs.

H2. PEU plays a positively significant influence on the attitude of PSEFLTs.

Subjective norms (SN)

In the Theory of Planned Behavior (TPB), subjective norms (SN) highlight the social influences shaping teachers' decisions, such as encouragement or pressure from colleagues, supervisors, or institutional policies to integrate AI (Fishbein & Ajzen, 2010). Recent empirical studies confirm that SN, individuals' perceptions of social forces to engage in or avoid certain behaviors, exerts a significant positive effect on teachers' intentions to adopt AI in educational practice (Ma & Lei, 2024; Wang et al., 2024). Teachers are thus more inclined to use technology for collaboration, professional support, or to avoid isolation within their institutions. According to Baddar and Khan (2023), this suggests that peer pressure also shapes teachers' attitudes toward technology. People are more likely to adopt behaviors that strengthen connections with individuals they value (Aptyka & Großschedl, 2022). Hence, attitudes and perceptions are often shaped by social groups with which individuals identify (Baddar & Khan, 2023). Pre-service English teachers (PETs), therefore, are likely to align their attitudes with the expectations of significant others as well as with their own behavioral goals (Aptyka & Großschedl, 2022). Consequently, we suggested that:

H3. SN play a positively significant influence on the attitude of PSEFLTs.

AI confidence (AIC)

AIC, or teachers' belief in their own abilities to use AI, is a key factor in determining their intention and readiness to include AI into teaching methods (Bergdahl & Sjöberg, 2025; Ashoori & Maghsoudi, 2025). Studies have consistently demonstrated that the willingness to use AI tools in the classroom is positively correlated with confidence. For instance, Sanusi et al. (2024) highlighted confidence as a significant predictor of AI adoption among educators, emphasizing the necessity for targeted professional development to enhance this confidence. Similarly, research indicates that teachers' confidence in teaching AI directly influences their intention to incorporate AI into their curricula (Ayanwale, 2022). Moreover, a study focusing on teachers' readiness to teach AI found that perceived confidence significantly predicts teachers' intention to do so (Rajapakse et al., 2024). Additionally, investigations into AI literacy among educators reveal that those with higher self-efficacy are more inclined to engage in professional learning activities related to AI (Du et al., 2024). Collectively, these findings underscore the critical role of building teachers' confidence through professional development and support to foster effective AI integration in education. Consequently, we hypothesize that:

H4. AI confidence plays a positively significant influence on the attitude of PSEFLTs.

Perceived benefits of AI in teaching (PBAIT)

PBAIT encompass the broader advantages that teachers associate with AI, such as its ability to facilitate personalized learning, automate administrative tasks, and provide real-time feedback to students (Zawacki-Richter et al., 2021). Teachers' desire and readiness to include AI into their teaching techniques are greatly influenced by their opinions on the advantages of AI in the classroom. Studies have shown that when teachers see how AI may improve teaching efficiency, personalize learning experiences, and improve learners' engagement, they are more likely to implement AI technologies in the classroom. As an example, previous studies indicates that PBAIT is a strong predictor of teachers' intention to use AI tools for educational purposes (e.g. Bakhadirov & Alasgarova, 2024). Similarly, a study found that teachers are more motivated and prepared to integrate AI into their courses when they believe it can improve student learning results (Alshorman, 2024). Additionally, the perceived benefits of AI in higher education have been linked to a greater inclination among staff members to utilize AI in classrooms (Xu, 2025). In light of the debate above, this study puts up the following hypotheses:

H5. PBAIT plays a positively significant influence on the attitude of PSEFLTs.

Methodology

Research design

In order to create a model that captures the interactions between the six variables, attitude (AT), SN, PBAIT, PU, PEU, and AIC, this study uses the structural equation modeling (SEM) technique. Data were gathered using a survey questionnaire that included many items for each study model variable in addition to demographic inquiries (Figure 1).

Participants

Participants in the present study included 128 (45 females and 83 males) PSEFLTs with age range of 18 to 28 ($\bar{x}$ = 21.8). They were majoring in TEFL at three branches of Teacher Education University in Iran (Mazandaran, Markazi, and Tehran). Convenience sampling was adopted in selecting the participants. Table 1 displays the demographic information for the participants.

Figure 1.
Proposed theoretical model for assessing PSEFLTs' attitude to integrate AI

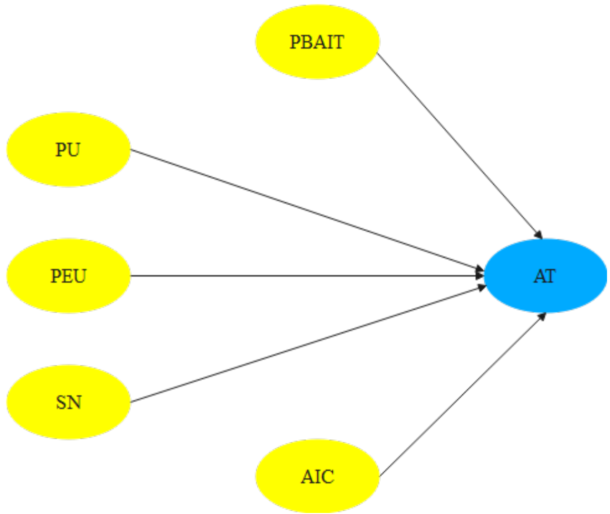


Table 1.
Demographic information of the participants

Category	Subcategory	Frequency	percentage
Gender	Female	45	.35
	Male	83	.65
Academic year	Freshman	31	.24
	Sophomore	43	.34
	Junior	37	.29
	Senior	17	.13
Location	Mazandaran	65	.51
	Tehran	37	.29
	Markazi	26	.20
Age range	18-20	74	.57
	21-23	48	.37
	24-26	5	.4
	26-28	3	.2

Research instrument

This work modified previous research instruments (Ayanwale et al., 2022, 2024; Chai et al., 2021; Schepman & Rodway, 2020, 2023) and developed five latent variables with 25 items. A Likert scale was used to assess the replies, with 1 denoting "strongly disagree" and 6 denoting "strongly agree." Two sections made up the survey. In the initial parts, background information was collected, including location, gender, age, and academic year. Subjective norms (4 items), AI confidence (3 items), perceived utility (3 items), perceived ease of use (3 items), and attitudes toward AI (5 items) of PSEFLTs were evaluated in the second phase of the survey (see Appendix).

Procedures for data collection and analysis

In order to gather data, the link to the Google Forms-created questionnaire was emailed to 167 PSEFLTs from various academic years, ranging from freshmen to seniors. The final number of participants was 128 PSEFLTs, of which 45 were women and 83 were males. Since each question had to be answered, participants had to finish the questionnaire before submitting it. Consequently, we collected an entire dataset devoid of any missing data. Because the participants could understand the English form of the questionnaire, the researchers decided not to use the translated version. Notably, the participants received guarantees that the information they provided and the survey answers they provided would be kept confidential.

The research data was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the factors impacting the PSEFLTs' attitudes on the usage of AI. This was accomplished by using the SmartPLS3 software. First, the overall model, structural model, and measurement model goodness-of-fit indices were presented. Following model confirmation, the research hypotheses were examined and, using structural equations, either accepted or denied.

Results

Examination of the measurement model

The measurement model is one that focuses on and measures the relationships between observable and latent variables. For this purpose, criteria such as the significance of the factor loadings between the items and their respective latent variables, convergent validity, reliability (including Cronbach's alpha and composite reliability) are utilized.

Significance of the factor loadings between items and their corresponding latent variables

To assess the model, the associations between the latent variables and their corresponding assessment items have been assessed using the outer model. The outer model examines the relationship between the items, or the questionnaire questions, and the constructs. In fact, until it is demonstrated that the questionnaire items adequately measure the latent variables, the relationships cannot be tested. To demonstrate that the latent variables had been accurately assessed, the outer model was employed. The standardized factor loadings and the t-values between all the items and their corresponding latent variables are presented in Table 2. If the factor loading is less than 0.3, the relationship is considered weak; a factor loading between 0.3 and 0.6 is considered acceptable, and a factor loading more than 0.6 is highly desirable (Neupan, 2014).

Table 2.
Factor loading values of the external model of latent variables

latent variable	Item	Factor Loading	t-value
AT	AT1	0.926	43.087
	AT2	0.944	79.755
	AT3	0.945	78.110
	AT4	0.870	24.905

	AT5	0.845	23.756
PU	PU1	0.911	53.064
	PU2	0.925	44.087
	PU3	0.872	20.656
PEU	PEU1	0.880	28.252
	PEU2	0.848	20.504
	PEU3	0.924	43.429
SN	SN1	0.867	25.238
	SN2	0.873	28.691
	SN3	0.894	27.384
	SN4	0.840	25.899
PBAIT	PBAIT1	0.722	9.759
	PBAIT2	0.689	8.895
	PBAIT3	0.854	27.388
	PBAIT4	0.839	28.969
	PBAIT5	0.816	19.344
	PBAIT6	0.799	17.021
	PBAIT7	0.842	24.837
AIC	AIC1	0.858	23.490
	AIC2	0.946	54.661
	AIC3	0.941	57.939

Note. AT: attitude; PU: perceived usefulness; PEU: perceived ease of use; SN: subjective norms; PBAIT: perceived benefits of AI in teaching; AIC: AI confidence

Based on the results of the measurement model presented in Table 2, the observed factor loadings for all items are greater than 0.5, indicating a satisfactory and acceptable correlation between the observable variables and their corresponding latent variables.

Convergent validity and reliability (Cronbach's Alpha and Composite Reliability)

For the AVE index, a minimum value of 0.5 is considered (Hulland, 1999), meaning that the latent variable explains at least 50% of the variance of its observable indicators. To assess internal consistency in the measurement model within the PLS method, a modern criterion known as Composite Reliability (CR) is used. Werts et al. (1974) introduced this index. Therefore, both of these criteria are employed to more accurately evaluate reliability in the PLS method. When each construct's composite reliability value is more than 0.7, the measurement model has the proper internal stability (Nunnally, 1978). For Cronbach's Alpha, values greater than 0.6 are considered acceptable. The results of these three criteria are presented in Table 3.

As seen in Table 3, based on the specified thresholds for all three criteria, it can be concluded that all the constructs in the study are at an appropriate level, confirming the suitability of the measurement models.

Table3.

Construct reliability and validity analysis

Items	**Cronbach's Alpha (>0.7)**	**Composite reliability(CR) (>0.7)**	**Average Variance Extracted (AVE) (>0.5)**	**Convergent Validity**
AT	0.945	0.959	0.822	Valid

PBAIT	0.903	0.924	0.635	Valid
PEU	0.864	0.915	0.782	Valid
PU	0.887	0.930	0.815	Valid
AIC	0.904	0.940	0.839	Valid
SN	0.892	0.925	0.754	Valid

Discriminant validity (Fornell and Larcker Method)

Another important criterion that determines validity is the extent of the relationship between a construct and its indicators compared to its relationship with other constructs. A model with acceptable discriminant validity indicates that a construct has a stronger interaction with its own indicators than with other constructs in the model. Fornell and Larcker (1981) state that discriminant validity is considered acceptable when the AVE for each construct is greater than the shared variance between that construct and other constructs (i.e., the squared correlation coefficient between constructs).

In the PLS software, this is assessed using a matrix where the cells contain the correlation coefficients between constructs and the square root of the AVE for each construct. The model is considered to have acceptable discriminant validity when the values on the main diagonal are greater than the values in the corresponding off-diagonal cells.

Table 4.
Discriminant validity test (the Fornell-Larcker)

	Attitude	PBAIT	PEU	PU	SE	SN
AT	0.907					
PBAIT	0.699	0.797				
PEU	0.650	0.561	0.884			
PU	0.663	0.459	0.422	0.903		
AIC	0.442	0.305	0.249	0.362	0.916	
SN	0.640	0.463	0.386	0.549	0.398	0.869

Using the Fornell and Larcker (1981) technique, the findings of the discriminant validity assessment are shown in Table 4. As observed, the square root of the AVE for the latent variables in this study, which are placed in the cells along the main diagonal of the matrix, is higher than the correlation values found in the off-diagonal cells below and to the left of the main diagonal. Therefore, it can be stated that, in the above model, the constructs (latent variables) interact more strongly with their own indicators than with other constructs. In other words, the discriminant validity of the model is at an acceptable level.

Examination of the structural model

The structural model represents the relationships between the latent variables. The criteria used in this model are as follows:

R2 (coefficient of determination) for dependent latent variables (explained variance) R^2 indicates the percentage of variation in the dependent variable that is explained by the independent variable. It is a measure of the impact an exogenous variable has on an endogenous variable, providing insight into how much of the variation in the endogenous variable is explained by the exogenous variable.

Table 5.
The coefficient of determination of the proposed model

	R Square	R square Adjusted
Intention	0.737	**0.723**

As can be observed in Table 5, the R^2 value for the construct Intention is 0.733, which indicates that the model is suitable.

Q2 (Stone-Geisser criterion)

The Q^2 value should be calculated for all endogenous constructs in the model. If the Q^2 value is zero or less, it indicates that the relationships between other constructs in the model and that endogenous construct are not well explained, suggesting that the model requires adjustment. The Q^2 value for the endogenous construct Intention is 0.589, which indicates the structural model is appropriate.

Effect size (F2)

This criterion determines the strength of the relationship between constructs in the model. The values of 0.02, 0.15, and 0.35 denote that one construct has small, medium, and substantial effects on another, respectively. The results, as presented in Table 6, indicate that the model is acceptable.

Table 6.
F2 coefficients of research variables

Influential variable	Affective variable	F^2
AT	Attitude	-
PBAIT	Attitude	0.205
PEU	Attitude	0.170
PU	Attitude	0.154
AIC	Attitude	0.034
SN	Attitude	0.107

Goodness-of-Fit Indices for the Overall Model

The goodness-of-fit indices for the overall model are reported as follows:

Overall Fit Criterion (GOF)

The overall fit criterion is used to reduce the difference between the observed and reproduced covariance matrices, which is a concept that does not exist in PLS. However, Tenenhaus et al. (2004) introduced the overall fit index for assessing the model's fit. The overall fit index can be calculated by taking the geometric mean of the average shared variance and R^2. For this index, the values of 0.10, 0.25, and 0.36 for this index are regarded as weak, moderate, and strong, respectively.

Standardized Root Mean Square Residual (SRMR)

Values less than 0.08 indicate a good fit for the model.

Normalized Fit Index (NFI)

Values greater than 0.90 for this index indicate an acceptable model fit. The results of the overall model fit are reported in Table 7, which indicates that the overall model of the research is satisfactory.

Table 7.
The GoF analysis results

	SRMR < 0,08	NFI > 0,9	GoF
Saturated Model	0.068	0.982	0.758

The results of the PLS-SEM analysis for the research model are presented in Figures 2 and 3.

Figure 2.
The factor loading coefficients results of the final research model

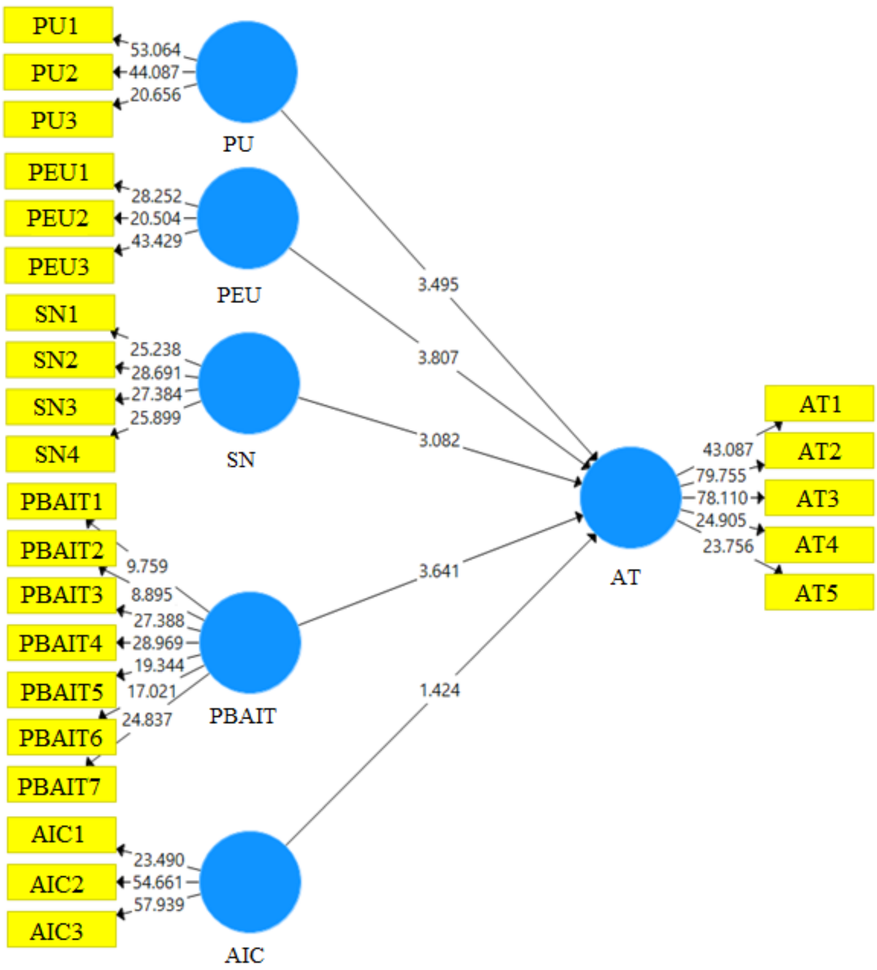
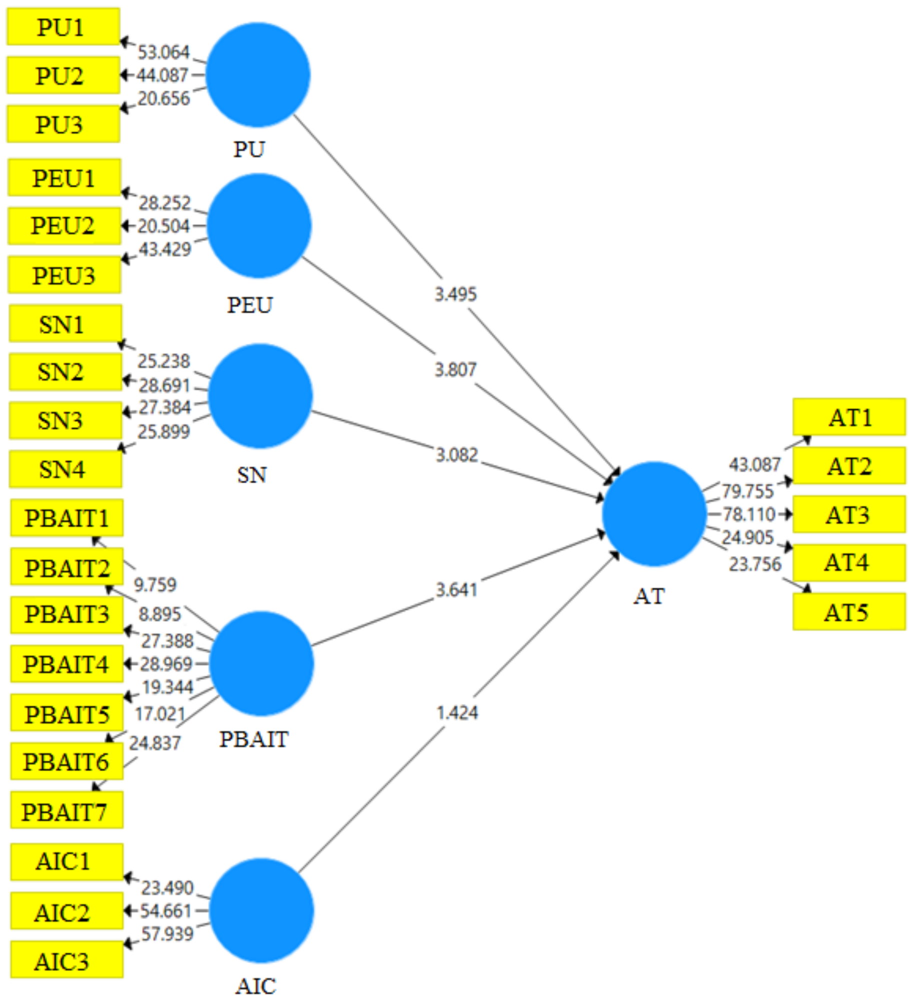


Figure 3.
T-test results of the final research model



Testing hypotheses

After examining the goodness-of-fit of the measurement models, structural models, and the overall model, the researcher is allowed to test and evaluate the hypotheses of the study. Therefore, the effects of the variables were assessed using structural equation modeling, considering both significance values for hypothesis testing and standardized coefficients to assess the strength of the effects of variables on each other. The results are presented in Table 8.

The research findings indicate the confirmation of 4 hypotheses ($p < 0.05$) and the rejection of the fifth hypothesis ($p > 0.05$). According to Table 8, the following results were observed:

Hypothesis 1: The positive and direct effect of PU on AT, with a coefficient of .257 and a test statistic of 3.495, was confirmed. Therefore, Hypothesis 1 is accepted.

Hypothesis 2: The positive and direct effect of PEU on AT, with a coefficient of 0.263 and a test statistic of 3.807, was confirmed. Therefore, Hypothesis 2 is accepted.

Hypothesis 3: The positive and direct effect of SN on AT, with a coefficient of .216 and a test statistic of 3.082, was confirmed. Therefore, Hypothesis 3 is accepted.

Hypothesis 4: The positive and direct effect of PBAIT on AT, with a coefficient of 0.302 and a test statistic of 3.641, was confirmed. Therefore, Hypothesis 4 is accepted.

Hypothesis 5: The positive and direct effect of AIC on AT, with a coefficient of 0.105 and a test statistic of 1.424, was rejected. Therefore, Hypothesis 5 is rejected.

Table 8.
The results of significance analysis

H	Relationship	Path	*t*-value	*p*-value	Direction	Decision
H1	PU→ AT	0.257	3.495	0.001	Positive	Proved
H2	PEU→ AT	0.263	3.807	0.000	Positive	Proved
H3	SN→ AT	0.216	3.082	0.002	Positive	Proved
H4	PBAIT→ AT	0.302	3.461	0.000	Positive	Proved
H5	AIC→ AT	0.105	1.424	0.155	Positive	Rejected

Discussion

The present study provides valuable insights into PSEFLTs' attitudes toward the adoption of AI in language education. The findings demonstrate that PU, PE, SN, and PBAIT significantly influence attitudes toward AI integration in educational settings. However, AIC did not have a statistically significant impact on attitudes. These findings offer an important contribution to the expanding body of literature on AI in education.

Concerning the first and second hypotheses, our study corroborates the TAM (Davis, 1989) by confirming that PU and PEU are crucial determinants of teachers' attitude towards AI. This is consistent with the results of Nja et al. (2023), Al Darayseh, (2023), Sanusi et al. (2023) who found that both PU and PEU are interrelated and significantly affect teachers' attitudes. In a similar study, According to Wijnen et al. (2021), school teachers' attitudes about technology use are greatly influenced by both PU and PEU, with PU having a particularly strong effect on their intentions to use technology into their lesson plans. In a similar vein, Chai et al. (2020) conducted a study on Chinese secondary school students and discovered that perceived usefulness significantly impacts students' attitudes towards using AI technology. When students believe that AI can improve their productivity and outcomes, they are more likely to have a favorable disposition towards learning it. Similarly, perceived ease of use also has a crucial role in influencing students' attitudes. If students feel confident that they can easily learn and apply AI concepts, their overall attitude towards AI will be more positive. This confidence can stem from prior experiences or the way the curriculum is designed to facilitate learning.

The significant influence of SN on attitudes toward AI corroborates with the results of Adelana et al. (2024) and MA and Lei (2024), who highlighted that SN significantly affect attitudes towards using AI-based technologies. When teachers perceive that their peers and superiors expect them to adopt AI technology, they are more inclined to have a favorable attitude towards its use. In a similar study, Ramnarain et al. (2024) reported that SN significantly impact teacher education students' attitudes and intentions to adopt AI technologies, highlighting the importance of social influences in educational technology adoption. In a study carried out by Sanusi et al. (2024), they discovered that while SN can directly influence how individuals feel about teaching AI, they can also do so indirectly by enhancing personal relevance and self-efficacy, which are critical components of attitude formation, suggesting that SN have both direct and indirect effects on attitudes.

The research findings on the effect of PBAIT on PSEFLTs' attitudes toward AI corroborate previous studies. Recent studies have highlighted the significant impact of PBAIT on the attitudes of both pre-service and in-service teachers (Bae et a., 2024; Hwang et al., 2020; Luckin, 2017). Educators who recognize the benefits of AI, like individualized instruction, efficient administrative support, and enhanced student involvement, tend to exhibit more positive attitudes toward its incorporation into educational settings (Luckin, 2017). For instance, in a study conducted by Chiu et al. (2021), it was found that teachers acknowledged AI's potential to streamline administrative tasks and provide tailored learning experiences, leading to increased acceptance of AI tools in the classroom. Similarly, research by Bae et al. (2024) indicated that PSTs perceived generative AI tools as beneficial for creating engaging instructional materials, which positively influenced their readiness to use such technologies in their future teaching practices. These findings corroborate with Hwang et al. (2020) and Luckin (2017) whose studies suggest that highlighting the practical benefits of AI can play a pivotal role in shaping educators' attitudes and promoting the adoption of AI-driven educational tools.

A surprising finding of our study was that AIC did not have a significant effect on PSEFLTs' attitudes towards AI (H6), contradicting prior research by Bandura and Wessels (1997) and Kim et al. (2019), who suggested that confidence is a key predictor of technology adoption. This discrepancy could be attributed to the specific context of our study, where PSTs, despite possessing general technological confidence, may still lack the pedagogical knowledge required to integrate AI effectively into language teaching. In other words, while these PSTs may feel comfortable using AI for personal or general educational purposes, they might struggle to connect its functionalities with sound pedagogical practices, leading to uncertainty in its classroom application. This is particularly relevant in English language teaching (ELT), where effective integration of AI requires not only technical proficiency but also an understanding of language acquisition theories, classroom interaction patterns, and student engagement strategies.

The results also align with findings by Tatar et al. (2024), who reported that while teachers may express confidence in using AI-driven tools for personal learning, they often struggle with their instructional application due to insufficient training. Similarly, Kallunki et al. (2024) noted that while teachers recognize AI's potential, they often feel unprepared to leverage it effectively in classroom settings. These insights highlight the need for structured training programs that equip PSTs with both technological proficiency and pedagogical strategies for AI integration.

Conclusion and implications

This study offers insightful information about the attitudes of PSEFLTs toward the adoption of AI in language education, highlighting the significant influence of PU, PEU, SN, and PBAIT on their attitudes. However, AIC did not have a statistically significant effect, suggesting that while PSEFLTs may recognize AI's potential, they may lack the necessary pedagogical and technical training to implement it effectively. These findings underscore the need for teacher education programs to integrate AI-focused pedagogical strategies that enhance both technological proficiency and instructional application. Institutions should offer hands-on training, workshops, and AI-integrated lesson planning activities to bridge the gap between theory and practice. Additionally, policymakers must establish supportive frameworks that promote AI adoption while addressing concerns related to technological readiness, ethical considerations, and potential implementation challenges. Future research should explore longitudinal studies to assess how direct exposure to AI in teaching influences long-term attitudes and pedagogical practices. By fostering AI literacy and equipping pre-service teachers with relevant competencies, educational stakeholders can ensure that AI technologies are effectively utilized to enhance language learning outcomes.

Limitations of the study

Despite its contributions, this study has certain limitations that should be considered. The research primarily relies on survey data, which may be subject to self-reporting biases, as participants might provide socially desirable responses rather than reflecting their true attitudes and experiences. Additionally, the study focuses on a specific group of PSTs in Iran, which limits the generalizability of the findings to other educational settings and cultural contexts. The study also does not account for external factors such as institutional infrastructure, access to AI tools, and prior exposure to technology, all of which could influence PSTs' attitudes toward AI adoption. Furthermore, PSEFLTs' attitudes have been documented at a particular moment in time, making it challenging to predict how they would evolve as educators get more familiar with AI in the classroom.

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Appendix

Appendix. Survey Questionnaire

Section 1:

What is your gender? □ male □ female

What is your academic year? □ freshman □ sophomore □ junior □ senior
What is your age? □ 18-20 □ 21-23 □ 24-26
Where are you from? □ Tehran □ Mazandaran □ Markazi

Section 2:

Direction: Please indicate the degree to which you agree or disagree with each statement.

Strongly Agree = 6	Agree = 5	Somewhat Agree = 4
Somewhat Disagree = 3	Disagree = 2	Strongly Disagree =1

	Items	6	5	4	3	2	1
	Attitude towards AI						
1.	Using AI is pleasant.						
2.	I find using AI to be enjoyable.						
3.	I have fun using AI.						
4.	AI makes teaching more interesting.						
5.	I look forward to those aspects of my job that requires me to use AI.						
	Perceived Usefulness (PU)						
6.	Using AI enables me to accomplish tasks more freely.						
7.	Using AI enhances my effectiveness.						
8.	Using AI increases my productivity.						
	Perceived Ease of Use (PEU)						
9.	I find it easy to get AI-based applications to do what I want it to do.						
10.	Interacting with AI applications does not require a lot of mental effort.						
11.	I find AI applications easy to use.						
	AI confidence						
12.	I am confident I can introduce the most complex materials about AI in class.						
13.	I believe that I can succeed in demystifying AI for students if I try hard enough.						
14.	I am confident that I will support students learning of AI in my class.						
	Perceived benefits of AI in teaching						
15.	I can use AI to get things done more quickly.						
16.	Using AI increases my effectiveness and research productivity.						
17.	AI is useful for teaching and learning activities.						
18.	AI can be used to meet students' differences.						
19.	AI can be used to enhance student self-learning.						

20.	AI can be used to evaluate students and provide them with feedback.						
21.	AI provides automatic correction of certain types of coursework that frees up the teacher’s time for other tasks.						
	Subjective norms						
22.	People whose opinions I value will encourage me to use AI.						
23.	My peers and/or parents will encourage me to participate in innovative AI-based activities.						
24.	People who are important to me will support me to use AI.						
25.	My course mates feel that learning how to work with AI in education is necessary.						