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Pre-service teachers' behavioral intentions toward AI integration: an extension of the Technology Acceptance Model

Intenciones conductuales de los futuros docentes hacia la integración de la IA: una extensión del Modelo de Aceptación Tecnológica

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Abstract

Artificial Intelligence (AI) has the potential to significantly enhance English language instruction and learning in classrooms. Despite the growing interest in AI in education, little is known about pre-service teachers' (PSTs) intentions to adopt AI in their future classrooms. This study examined the behavioral intention of pre-service English as a foreign language teachers (PSEFLTs) to use AI to enhance English instruction and learning in their future classrooms. By examining factors such as AI anxiety, perceived utility, perceived ease of use, AI self-efficacy, AI literacy, and AI readiness, this study extends the Technology Acceptance Model (TAM), which serves as a theoretical framework, to better understand PSEFLTs' intentions to adopt AI. A structured survey was administered to 100 PSEFLTs across three different Iranian Teacher Education Universities. Using partial least squares-structural equation modeling (PLS-SEM), results showed that PSEFLTs' behavioral intentions to adopt AI are positively influenced by AI self-efficacy, perceived usefulness, perceived ease of use, AI literacy, and AI readiness. However, AI anxiety was found to be an insignificant predictor of behavioral intention. These results highlight how important it is for teacher education programs to promote AI literacy, and boost self-efficacy in order to guarantee successful AI integration. By extending TAM and tackling the understudied topic of PSTs' adoption of AI technologies, the study adds to the body of literature.

Keywords: *AI Integration, Behavioral Intentions, Teacher training, Technology Acceptance Model (TAM), Technology adoption*

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Resumen

La Inteligencia Artificial (IA) posee el potencial de mejorar significativamente la enseñanza y el aprendizaje del idioma inglés en el aula. A pesar del creciente interés en la IA dentro del ámbito educativo, poco se sabe sobre las intenciones de los futuros docentes de adoptar la IA en sus futuras aulas. Este estudio examinó la intención conductual de los futuros profesores de inglés como lengua extranjera (FPELT) para utilizar la IA con el fin de mejorar la enseñanza y el aprendizaje del inglés en sus futuras aulas. Al examinar factores como la ansiedad hacia la IA, la utilidad percibida, la facilidad de uso percibida, la autoeficacia en IA, la alfabetización en IA y la preparación para la IA, este estudio amplía el Modelo de Aceptación Tecnológica (TAM), que sirve como marco teórico, para comprender mejor las intenciones de los FPELT de adoptar la IA. Se administró una encuesta estructurada a 100 FPELT de tres universidades iraníes diferentes de formación del profesorado. Utilizando el modelado de ecuaciones estructurales por mínimos cuadrados parciales (PLS-SEM), los resultados mostraron que las intenciones conductuales de los FPELT de adoptar la IA están influenciadas positivamente por la autoeficacia en IA, la utilidad percibida, la facilidad de uso percibida, la alfabetización en IA y la preparación para la IA. Sin embargo, se encontró que la ansiedad hacia la IA no fue un predictor significativo de la intención conductual. Estos resultados resaltan la importancia de que los programas de formación del profesorado promuevan la alfabetización en IA y aumenten la autoeficacia para garantizar una integración exitosa de la IA. Al extender el TAM y abordar el tema poco estudiado de la adopción de tecnologías de IA por parte de los futuros docentes, el estudio contribuye al cuerpo de la literatura existente.

Palabras clave: *se incluirán un máximo de 5 palabras clave. Deben ser relevantes, concisas y representar con precisión el contenido del artículo, evitando la redundancia con el título o resumen.*

Introduction

Technology driven by AI is becoming more and more common, changing our thoughts, behaviors, and communication. The use of AI in education has increased dramatically, radically altering instructional strategies (Zhang & Aslan, 2021). For example, the rise of ChatGPT has sparked a lot of conversation. By providing individualized learning experiences and relieving teachers of administrative duties, ChatGPT and related AI tools have the potential to significantly impact education. Research on the advantages of AI in K–12 and higher education has increased since the COVID-19 pandemic, when it was essential for personalizing learning using student data (Peng et al., 2022).

Undeniably, teachers' intention to embrace new technologies is essential for educational innovation to succeed. Despite AI's infancy in K–12, it is imperative to integrate it from early education through high school (Sanusi et al., 2022). The emergence of AI creates new difficulties for researchers, educators, and policymakers in guaranteeing its appropriate application. Researchers are actively trying to make sure teachers use AI-driven technology effectively, even though examining state policies is essential for curriculum acceptance (Sanusi et al., 2022). (Xia et al., 2022).

Even with the abundance of AI resources, teachers frequently lack the knowledge needed to teach students with AI (Sanusi et al., 2021). Researchers are looking into how professional development (PD) programs and co-designed materials can prepare teachers because of this important knowledge gap (Lee & Perret, 2022). As important as professional development is, it's equally important to know whether pre-service teachers (PSTs), who are future teachers, intend to incorporate AI into their lesson plans. Implementing new course material is impossible without teacher support (Lin & Van Brúmeles, 2021). Thus, obtaining PSTs' perspectives on their behavioral intention to incorporate AI aids in determining the elements that support its successful application in the classroom.

Research on the perspectives of PSTs is limited, despite studies examining the intentions of students to learn AI (e.g., Maheshwari, 2024) and in-service teachers to integrate AI (e.g., Ayanwale et al., 2024). However, PSTs' behavioral intentions will play a major role in future AI implementation, so their opinions are vital. By investigating PSTs' motivations, we can forecast AI adoption rates and spot early obstacles and enablers, resulting in more successful professional development initiatives (Maheshwari, 2024). Additionally, it assists in identifying knowledge and skill gaps in current AI-related teacher preparation curricula, allowing for the development of pertinent educational materials that give aspiring educators the pedagogical and technological know-how they need (Zawacki-Richter et al., 2021). Without this knowledge, we run the risk of graduating educators who are not prepared to fully utilize AI's potential.

Examining the primary determinants of PSTs' behavioral intentions to implement AI in schools, this study focuses on AI anxiety, perceived usefulness, perceived ease of use, AI self-efficacy, AI literacy, and AI readiness. The purpose of the study is to determine how these factors influence PSTs' behavioral intentions regarding the use of AI in the classroom in Iran. The study will provide a comprehensive understanding of the opportunities and challenges PSTs face when integrating AI by analyzing these elements. The study will also pinpoint how teacher education programs can help address these issues and provide guidance on how to best tailor these programs to better prepare aspiring teachers for the demands of an AI-enhanced classroom.

Literature Review

AI is transforming education by providing creative answers to traditional problems in teaching and learning. By evaluating data to determine strengths and weaknesses, technologies such as adaptive learning platforms and intelligent tutoring systems tailor education to the needs of each individual student (Holmes & Tuomi, 2022). According to research, AI improves academic performance, motivation, and engagement while also offering immediate feedback that is essential for dynamic learning (Slimi & Carballido, 2023). However, algorithmic bias and data privacy are ethical issues brought up by AI integration (Zawacki-Richter et al., 2021).

For English language teaching (ELT), AI has substantial pedagogical advantages. Natural language processing tools improve acquisition by offering real-time language support, correction, and customized exercises (González-Lloret, 2022; Saz-Pérez & Pizà-Mir, 2024a). By simulating conversations, chatbots and virtual assistants provide low-stress practice settings that increase engagement by reducing the affective filter (Holmes & Tuomi, 2022; Deng, 2024). However, relying too much on AI could result in the loss of essential human interaction that is required to build interpersonal relationships and communication skills (Deng, 2024).

Administratively, AI improves retention by streamlining institutional processes and assisting in the timely identification of at-risk students for intervention (Jatileni et al., 2024). Additionally, AI streamlines scheduling and grading, freeing up teachers to concentrate on instruction (Holmes & Tuomi, 2022). AI must be carefully incorporated into educational institutions to ensure that it enhances rather than replaces teachers (Ayanwale et al. 2024). A balanced approach that places a high priority on ethics, fair access, and improved outcomes for all students requires constant research and discussion between educators and legislators.

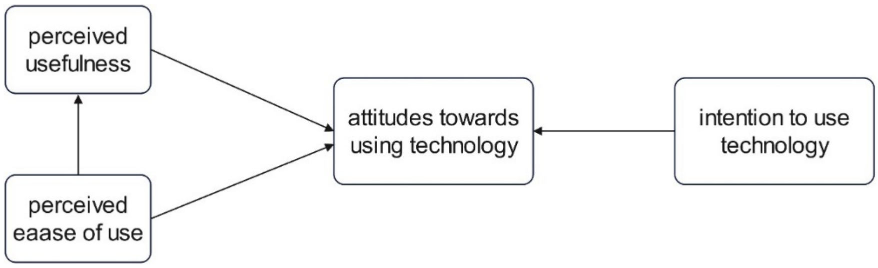
Theoretical Framework: Technology Acceptance Model (TAM)

One popular framework for understanding technology adoption in information systems research is the Technology Acceptance Model (TAM) (Davis, 1989). Perceived usefulness and perceived ease of use are identified as important factors that influence the adoption of technology. Perceived ease of use reflects how effortless technology is, while perceived usefulness refers to the idea that technology improves performance. Users' attitudes are shaped by these perceptions, which in turn affect their intention and actual use. While these two constructs were initially the focus of TAM

(Figure 1), subsequent extensions have included elements like social influence and AI self-efficacy, providing a more complete picture of technology adoption in a variety of contexts.

Figure 1

The Technology Acceptance Model. Figure adapted from Davis (1989, p. 985)



Hypothesis Development

AI anxiety (AIA)

Technology adoption often elicits mixed emotions, ranging from optimism to anxiety (Dai et al., 2020). AI-related anxiety, or technophobia, arises from uncertainties in AI's development, autonomy, and human exclusion (Johnson & Verdicchio, 2017; Terzi, 2020). Misconceptions about AI, poor design, and reduced human involvement intensify this fear (Lemay et al., 2020). While Chai et al. (2020) found no link between AI anxiety and behavioral intention among students, Kin et al. (2020) reported that computer anxiety negatively affects self-esteem and intention. Katsarou (2021) emphasizes that technophobia is a significant indicator of digital literacy and user intention. As a result, we proposed the hypothesis below:

H1. PSTs' behavioral intention to use technology will be significantly impacted by AI anxiety.

Perceived Usefulness (PU) and Perceived Ease of Use (PEU)

Davis (1989) introduced the concepts of perceived usefulness and perceived ease of use, defining them as the extent to which individuals believe technology enhances productivity and is free of effort, respectively. These factors shape users' attitudes toward technology, with positive perceptions fostering favorable attitudes. Empirical studies consistently confirm that perceived usefulness and ease of use positively influence attitudes toward educational technologies, including AI tools (e.g., Ayanwale et al., 2022). As key antecedents of attitude, they indirectly affect behavioral intention to use technology, highlighting their significance in understanding technology adoption processes. Consequently, we put up the following hypothesis:

H2. PSTs' behavioral intention to use technology will be significantly impacted by Perceived usefulness.

H3. PSTs' behavioral intention to use technology will be significantly impacted by perceived ease of use.

AI Self-efficacy (AISE)

Self-efficacy, defined as one's belief in their ability to perform a task (Bandura, 1982), influences how effectively individuals engage in professional activities. In educational settings, higher self-efficacy is linked to greater use of innovative tools, including AI (Ayanwale et al., 2022). Rajapakse et al. (2024) found that AI self-efficacy positively correlates with teachers' readiness to adopt AI-driven instruction. Likewise, Ayanwale et al. (2024) and Lu et al. (2024) highlight that confidence in using AI fosters positive attitudes and willingness to integrate it. Since AI self-efficacy has positive impact on teachers' readiness, willingness and attitude to integrate AI into their classrooms, the following theory was put forth:

H4. PSTs' behavioral intention to use technology will be significantly impacted by AI self-efficacy.

AI Literacy (AIL)

AI literacy, a key element in AI integration in education, refers to individuals’ understanding of AI concepts and applications (Lin et al., 2025; Ng et al., 2021). Chai et al. (2021) describe AI-literate individuals as those capable of applying AI to solve problems. Long and Magerko (2020) expand this, defining AI literacy as a skillset involving the ability to use, evaluate, and interact with AI effectively across contexts. AI literacy has been shown to influence AI self-efficacy (Khan & Idris, 2019) and attitudes (Jan, 2018). However, its effect on pre-service teachers’ behavioral intention remains unexplored, leading to the following hypothesis:

H5. PSTs' behavioral intention to use technology will be significantly impacted by AI literacy.

AI Readiness (AIR)

AI readiness refers to the capacity to adapt to changes brought about by AI technologies and is recognized as a key factor influencing AI adoption (Kelly et al., 2023). Growing research has explored AI readiness among various groups, including educators (Ayanwale et al., 2022), professionals (Damerji & Salimi, 2021), and students (Chai et al., 2020, 2021). Specifically, teachers’ AI readiness significantly impacts their behavioral intention to adopt AI in educational contexts (Ayanwale et al., 2022). Building on this, the present study investigates its effect on PSTs’ behavioral intention to integrate AI, leading to the following hypothesis:

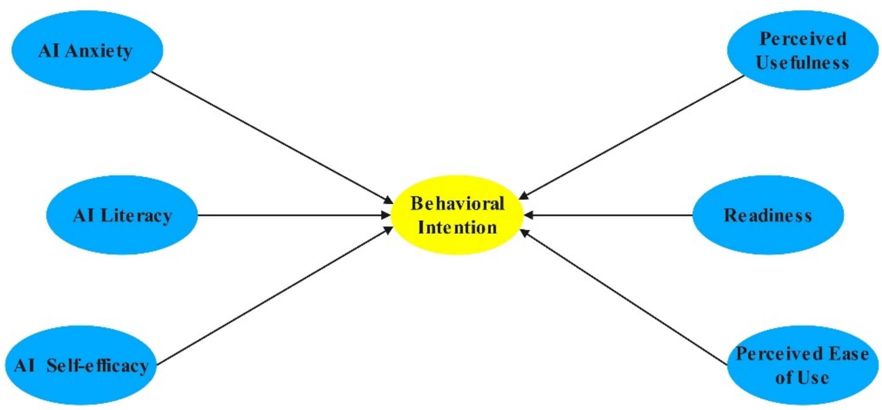
H6. PSTs' behavioral intention to use technology will be significantly impacted by AI readiness.

Methodology

Research design

To create a model that captures the interactions between the seven variables in this study—behavioral intention, perceived usefulness, perceived ease of use, AI self-efficacy, AI anxiety, AI readiness, and AI literacy—this study uses a structural equation modeling (SEM) technique. A survey questionnaire was used to collect data and it comprised several items for every variable in the study model as well as demographic questions (Figure 2).

Figure 2
Proposed theoretical model for assessing PSTs’ behavioral intention to integrate AI



Participants

Participants in the present study included 100 (21 females and 69 males) PSTs with age range from of 18 to 26 (x̄ = 21.2). They were majoring in TEFL at three branches of Teacher Education University in Iran (Mazandaran, Markazi, and Tehran). Due to practical constraints such as access to pre-service teachers in certain locations, convenience sampling was adopted in selecting the participants. Table 1 displays the demographic information for the participants.

Table 1
Demographic Information of the Participants

Category	Subcategory	Frequency/percentage
Gender	Female	31
	Male	69
Academic year	Freshman	31
	Sophomore	25
	Junior	28
	Senior	16
Location	Mazandaran	47
	Tehran	31
	Markazi	22
Age range	18-20	56
	21-23	38
	24-26	6

To ensure that the relative conveniently selected sample size of PSEFLTs (N = 100) with gender imbalance does not restrict the external validity of results reported under the observed effect sizes in the PLS-SEM analysis, a post hoc power analysis was conducted to assess the statistical power of the study using G*Power. The analysis indicated a power (1-β) of 0.84, above the conventional threshold of 0.80, suggesting the study was powerful enough to detect significant relationships.

Research Instrument

For the current study, six latent variables with 27 items were adapted from previous research (Ayanwale et al., 2022; Chai et al., 2021; Keramati et al., 2011). The original items were reviewed, piloted with 15 students, and slightly adjusted to ensure they were culturally and contextually appropriate for the Iranian setting, particularly for pre-service English language teachers. A Likert scale was used to rate the responses, with 1 indicating "strongly disagree" and 6 indicating "strongly agree." The survey was divided into two parts. Background data such as location, gender, age, and academic year was gathered in the first sections. In the survey's second section, PSTs' perceptions towards AI anxiety (4 items), perceived usefulness (3 items), perceived ease of use (3 items), AI literacy (4 items), AI self-efficacy (3 items), AI readiness (5 items), and behavioral intention (5 items) to use AI were assessed. Cronbach's alpha provided evidence of the survey's internal consistency. the reliability estimate of the whole scale was α=.91and the factors' reliability coefficients ranged from 0.78 to 0.94. Additionally, considering that the measurement method was mainly predicated on Likert scales, variance in the collected data may have been attributed to the instrumental limitations. Accordingly, common method bias was tested post hoc using exploratory factor analysis (unrotated). Since the results indicated that not a single factor did explain most variance (> 50%), it was concluded that common method bias is insignificant. These findings imply that the instrument employed in this study is regarded as a suitable instrument for gauging PSEFLTs' intention to include AI into future classes.

Procedures for Data Collection and Analysis

In order to collect data, 138 pre-service English language teachers (PSEFLTs) from different academic years, from freshmen to seniors, were provided the link to the questionnaire, which was created using Google Forms. Out of this total, 100 PSEFLTs, 31 women and 69 men, completed it, making up the final participant count. Participants had to answer all the questions before turning in the questionnaire because each one had to be completed. As a result, we gathered a whole dataset that was free of any missing information. The researchers chose not to administer the translated version of the questionnaire because the participants were able to understand the English form. Notably, the participants were given assurances that the data they submitted and the responses they gave to the survey would remain private.

To examine the factors influencing pre-service teachers' (PSTs) behavioral intention to adopt AI, Partial Least Squares-Structural Equation Modeling (PLS-SEM) was used for data analysis, with the SmartPLS 3 software employed for this purpose. First, the fit indices for the measurement model, structural model, and overall model were reported. After confirming the model, the research hypotheses were tested and either supported or rejected using structural equation modeling.

Results

Measurement Model:

The measurement model analyzes and measures the relationships between observed variables (indicators) and latent variables. To evaluate the measurement model, the following criteria are used:

- Significance of factor loadings between items and their associated latent variables.
- Convergent validity.
- Reliability, assessed through Cronbach's alpha and composite reliability coefficients.

Fit Indices for the Measurement Model

Significance of factor loadings between Items and their latent variables

To analyze the model, the relationships between latent variables and their corresponding indicators were first evaluated using the outer model. The outer model assesses the connections between indicators (questionnaire items) and constructs. This step ensures that the indicators properly measure the latent variables before testing their relationships.

The standardized factor loadings and t-values between all items and their associated latent variables are presented in Table 2.

- Factor loadings below 0.3 are considered weak.
- Factor loadings between 0.3 and 0.6 are acceptable.
- Factor loadings above 0.6 are highly desirable (Neupane, 2014).

The outer model ensures that the latent variables are accurately measured before the relationships between them can be tested.

Table 2
Factor Loading Values of the External Model of Latent Variables

latent variable	Item	Factor Loading	t-value
AIA	AIA1	0.769	6.702
	AIA2	0.814	8.204
	AIA3	0.858	15.999
	AIA4	0.843	19.130
PU	PU1	0.892	26.666

	PU2	0.931	49.829
	PU3	0.887	34.488
PEU	PEU1	0.852	20.731
	PEU2	0.883	36.565
	PEU3	0.925	51.895
AISE	AISE1	0.803	19.357
	AISE2	0.897	46.972
	AISE3	0.862	24.427
AIL	AIL1	0.852	18.933
	AIL 2	0.908	36.199
	AIL 3	0.899	31.543
	AIL 4	0.944	78.199
AIR	AIR1	0.767	22.351
	AIR2	0.885	23.682
	AIR3	0.745	8.222
	AIR4	0.869	14.766
	AIR5	0.741	7.418
BI	BI1	0.847	19.924
	BI2	0.848	23.878
	BI3	0.881	33.023
	BI4	0.909	38.594
	BI5	0.806	17.632

Note. AIA: AI anxiety; PU: perceived usefulness; PEU: perceived ease of use; AISE: AI self-efficacy; AIL: AI literacy; AIR: AI readiness; BI: behavioral intention

According to the results of the measurement model presented in Table (2), the observed factor loadings for all items exceed 0.5, indicating a satisfactory and acceptable correlation between the observed 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 acceptable (Holland, 1999), meaning that the latent variable explains at least 50% of the variance in its observed indicators. To evaluate the internal consistency of the measurement model in the PLS method, a more modern criterion known as Composite Reliability (CR) is employed. This index was introduced by Werts et al. (1974).

As a result, both criteria are used to better assess reliability in the PLS method. If the composite reliability for a construct exceeds 0.7 (Nunnally, 1978), it indicates acceptable internal stability for the measurement model, while Cronbach's alpha values higher than 0.6 are deemed acceptable. The results of these three criteria are presented in Table 3.

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
AIA	0.845	0.893	0.675	Valid
AISE	0.815	0.890	0.731	Valid
BI	0.911	0.934	0.738	Valid
AIL	0.922	0.945	0.812	Valid
PEU	0.864	0.917	0.787	Valid
PU	0.887	0.930	0.816	Valid
AIR	0.869	0.901	0.646	Valid

As observed in Table 3, considering the specified thresholds for all three criteria, it can be stated that all constructs in the study are at an acceptable level, confirming the adequacy and desirability of the measurement models.

Discriminant Validity (Fornell and Larcker Method)

The way a construct and its indicators relate to one another in comparison to other constructs is another crucial validity requirement. In a model, a concept is said to have acceptable discriminant validity if it interacts more strongly with its own indicators than with other constructs. According to Fornell and Larcker (1981), when the AVE value for each construct in the model is higher than the shared variance between that construct and other constructs, discriminant validity is at an acceptable level.

In the PLS software, this is examined using a matrix where the diagonal cells contain the square root of the AVE values for each construct, while the off-diagonal cells contain the correlation coefficients between constructs. A model has acceptable discriminant validity if the values on the diagonal (square root of AVE) are greater than the values below them in the matrix.

Table 4
Discriminant Validity Test (The Fornell-Larcker).

	AIA	AISE	BI	AIL	PEU	PU	AIR
AIA	0.822						
AISE	-0.344	0.855					
BI	-0.387	0.960	0.859				
AIL	-0.355	0.937	0.975	0.901			
PEU	-0.234	0.720	0.743	0.732	0.887		
PU	-0.364	0.964	0.981	0.968	0.731	0.904	
AIR	-0.324	0.627	0.661	0.620	0.378	0.661	0.804

Table 4 presents the results of the discriminant validity assessment using the Fornell and Larcker (1981) method. As observed, the square root of the AVE values for the latent variables in this study, which are located in the diagonal cells of the matrix, are higher than the correlation coefficients found in the lower-left cells of the matrix. Consequently, it can be said that in this model, the latent variables interact more strongly with their own indicators than with other constructs. Put differently, the discriminant validity of the model is at an acceptable level. Although the high correlation coefficients (e.g., between AIL and BI) reported in Table 4 may be attributed to multicollinearity, the Fornell-Larcker criterion (AVE > inter-construct correlations) and acceptable VIF values (< 3.3) (see Table 7) confirm discriminant validity and minimal multicollinearity bias. Instead, high correlations can be attributed to theoretical alignment between constructs (e.g., the role of AIL in shaping BI).

Structural Model Assessment

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

Coefficient of Determination (R^2) for Endogenous Latent Variables (Explained Variance)

The R^2 value indicates the percentage of variance in the dependent (endogenous) variable that is explained by the independent (exogenous) variable. Essentially, it is a measure of the impact of an exogenous variable on an endogenous variable.

Table 5
The Coefficient of Determination of the Proposed Model

	R Square	R square Adjusted
Behavioral Intention	0.977	0.976

As shown in Table 5, the R^2 value for the construct 'Behavioral Intention' is 0.977, indicating the model's adequacy.

Q^2 Criterion (Stone-Geisser Criterion)

The Q^2 value should be calculated for all endogenous constructs in the model. If the value is zero or less, it indicates that the relationships between the other constructs and the endogenous construct are not well-explained, suggesting the model requires improvement. The Q^2 value for the endogenous construct Behavioral Intention is 0.703, which demonstrates the adequacy of the structural model.

Effect Size (F^2)

This criterion evaluates the strength of the relationship between constructs in the model. Values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively. The results, presented in Table 6, confirm the acceptability of the research model.

Table 6
F^2 Coefficients of Research Variables

Influential variable	Affective variable	F^2
AIA	BI	0.038
AISE	BI	0.087
BI	BI	-
AIL	BI	0.389
PEU	BI	0.035
PU	BI	0.213
AIR	BI	0.042

Variance Inflation Factors

Variance inflation factors (VIFs) were examined to endure that the findings are not misinterpreted due to the existence of multicollinearity among predictor constructs. VIF values, as reported in Table 7, were all less than 3.3 (ranging between 1.12 and 2.84), indicating acceptable levels of collinearity.

Table 7
Variance Inflation Factors (VIF) for Predictor Constructs

Construct	VIF
AI Anxiety (AIA)	1.12
Perceived Usefulness (PU)	2.84
Perceived Ease of Use (PEU)	1.67
AI Self-Efficacy (AISE)	1.45
AI Literacy (AIL)	2.31
AI Readiness (AIR)	1.53

Overall Model Fit Indices

The overall model fit indices are reported as follows:

1. **Goodness of Fit (GoF)**

   This criterion reduces the difference between the observed and reproduced covariance matrices, which is not an assumption in PLS. However, Tenenhaus et al. (2005) introduced the GOF index to evaluate model fit. GOF can be calculated as the geometric mean of the average shared variance and R^2. For this index, values of 0.01, 0.25, and 0.36 are described as weak, moderate, and strong, respectively.

2. **Standardized Root Mean Square Residual (SRMR)**

   Values less than 0.08 indicate a good model fit.

3. **Normed Fit Index (NFI)**

   Values greater than 0.9 indicate a good model fit.

The fit results, presented in Table 8, confirm that the overall research model is satisfactory.

Table 8
The GoF Analysis Results

	SRMR < 0,08	NFI > 0,9	GoF
Saturated Model	0.07	0.941	0.852

The PLS-SEM analysis results for the research model are presented in Figures 3 and 4.

Figure 3
The Factor Loading Coefficients Results of the Final Research Model

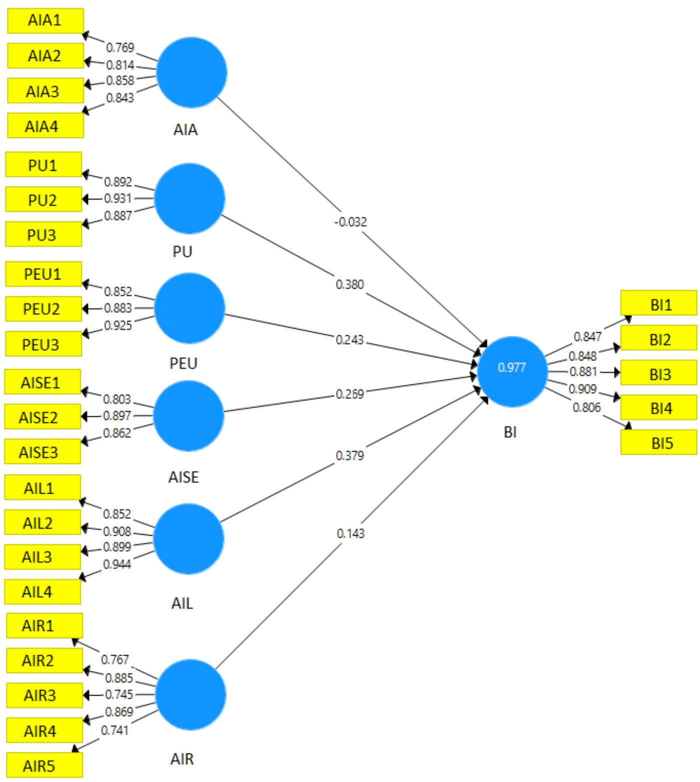
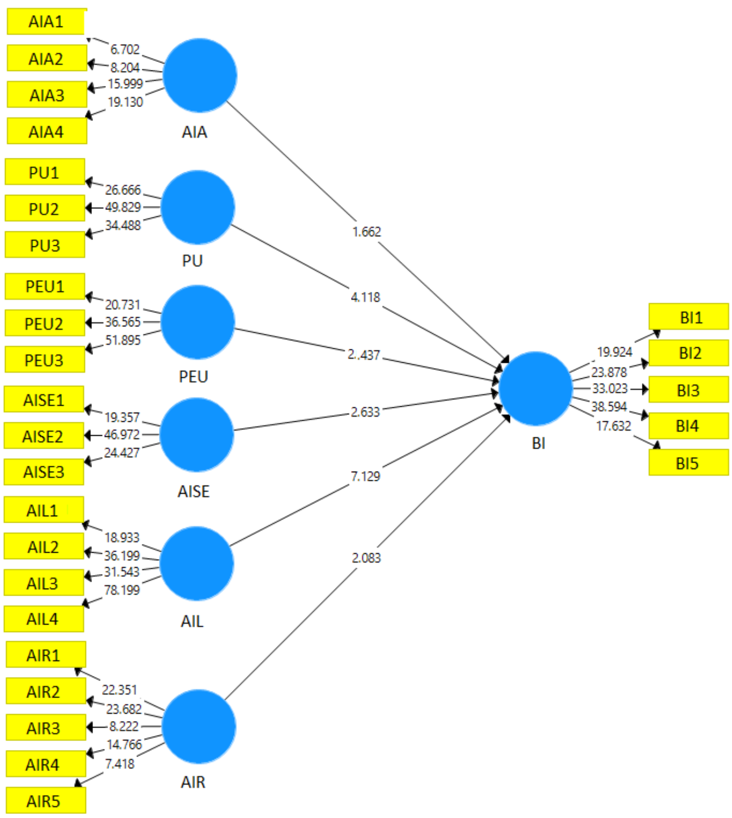


Figure 4
T-test Results of the Final Research Model



Hypotheses Testing

After evaluating the measurement, structural, and overall model fit, the researchers tested the research hypotheses using structural equation modeling (SEM), focusing on significance values to validate the hypotheses and standardized coefficients to determine the strength of the relationships. As depicted in Table 9, the results showed that five hypotheses were supported ($p < 0.05$), while the first hypothesis was rejected ($p = .08 > 0.05$). Specifically, Hypothesis 1, which posited a negative and direct effect of AI Anxiety on Behavioral Intention, was rejected with a coefficient of -0.032 and a t-statistic of 1.662. Hypothesis 2, proposing a positive and direct effect of Perceived Usefulness on behavioral Intention, was supported with a coefficient of 0.380 and a t-statistic of 4.118. Hypothesis 3, suggesting a positive and direct effect of Perceived Ease of Use on Behavioral Intention, was supported with a coefficient of 0.243 and a t-statistic of 2.437. Hypothesis 4, which examined the positive and direct effect of AI Self-Efficacy on Behavioral Intention, was confirmed with a coefficient of 0.269 and a t-statistic of 2.633. Hypothesis 5, investigating the positive and direct effect of AI Literacy on Behavioral Intention, was also supported with a coefficient of 0.379 and a t-statistic of 7.129. Lastly, Hypothesis 6, exploring the positive and direct effect of AI Readiness on Behavioral Intention, was supported with a coefficient of 0.143 and a t-statistic of 2.083.

Table 9
Results of Significance Analysis

H	Relationship	Path	*t*-value	*p*-value	Direction	Decision
H1	AIA→ BI	-0.032	1.662	0.083	Negative	Rejected
H2	PU→ BI	0.380	4.118	0.000	Positive	Proved
H3	PEU→ BI	0.243	2.437	0.042	Positive	Proved

H4	AISE→ BI	0.269	2.633	0.011	Positive	Proved
H5	AIL→ BI	0.379	7.129	0.000	Positive	Proved
H6	AIR→ BI	0.143	2.083	0.044	Positive	Proved

Discussion

Identifying pre-service teachers' (PSTs) behavioral intention to adopt AI is a crucial factor for its integration into educational settings. Currently, there are no studies in the literature that specifically examine PSEFLTs' behavioral intention to incorporate AI. The factors influencing their intention to use AI, as identified in this study, include AI anxiety, perceived usefulness, perceived ease of use, AI self-efficacy, AI readiness, and AI literacy. Six hypotheses were proposed in this context, with five being confirmed and one rejected.

The findings show that AI anxiety does not significantly affect PSEFLTs' behavioral intention to use AI. It contrasts with prior findings pertaining to technophobia or technology resistance (e.g., Johnson & Verdicchio, 2017; Kin et al., 2020) while echoing others (e.g., Chai et al., 2020). This discrepancy might be due to the sample characteristics and contextual factors. That is, PSEFLTs may stand technological uncertainty due to their exposure to the pedagogical training they receive, as reflected in PSEFLTs' AIL, emphasizing digital tool application (Ayanwale et al., 2022). This also aligns with Chai et al. (2021), who found that knowledge-based constructs (e.g., AI literacy) mediate anxiety's effects. As Bandura (1982) noted, self-efficacy, a strong predictor of BI in this study, can alleviate anxiety as PSEFLT feel more confident in facing technological tools. In addition, the significant role of AIR and AIL explains the insignificant role of AI, as PSEFLTs' practical competencies assist them overcome psychological barriers.

The results of the second and third hypotheses corroborate TAM's core claims, which hold that instructors' behavioral intention to incorporate AI in their classes is significantly influenced by perceived usefulness and perceived ease of use, as articulated by Davis (1989) and proved in studies such as Ayanwale et al. (2022), Maheshvari (2024), Ma and Lei (2024), Sanusi et al. (2023), and Zhang et al. (2023). When educators find out that AI-related technology can enable personalized learning experiences and provide immediate feedback, such technology will most likely be seen in a positive manner (Holmes & Tuomi, 2022; Slimi & Carballido, 2023). However, when educators view AI technology as complex, cumbersome, and therefore not worth deploying, such technology will most likely not gain acceptance (Venkatesh & Davis, 2000). According to previous studies, a high perceived ease of use and perceived usefulness have a positive relation with teachers' acceptance of educational technology, including AI technology (Ayanwale et al., 2024; Chai et al., 2021). When educators find out that AI can make lesson planning easier and enhance students' motivation without having to require a lot of technical expertise, such technologies will most likely gain acceptance (Zawacki-Richter et al., 2021).

In terms of the fourth hypothesis, the study reveals a robust connection between AI self-efficacy and the behavioral intention to utilize AI technologies by the PSEFLTs. As mentioned by Bandura (1982) AI self-efficacy is a key factor in building teachers' behavioral intentions toward AI application in their classrooms because it directly affects their self-assurance in the effective use of these technologies. It has been known that teachers who have more AI self-efficacy are more likely to adopt new tools, including AI, because they believe that they can deal with potential challenges easily, and use these technologies in a better way (Ayanwale et al., 2024). A study by Rajapakse et al. (2024) found a correlation between AI self-efficacy and teachers' readiness to use AI-based instruction methods. This is due to the fact that teachers who believe in their ability to use AI are more disposed to do so and work with AI in the right way. Furthermore, Ayanwale et al. (2022) emphasized that AI self-efficacy fosters a proactive attitude toward technology integration, enabling teachers to explore and utilize AI tools more effectively. This aligns with findings from Lu et al. (2024), which illustrate that educators' beliefs in their own abilities significantly influence their intention to experiment with AI applications, ultimately enhancing educational outcomes. The positive association of AI self-efficacy with behavioral intention is also reported by Ayanwale et al. (2024), Teo (2009), Teo and Zhou (2014), Yao and Wang (2024), who emphasized that a higher self-efficacy in technological skills yields greater adoption intentions. Moreover, in Makhitha's (2024) work. AI self-efficacy is presented as an essential factor for AI adaption. Furthermore, AI self-efficacy not only affects individuals' behavioral intention but also impacts collaborative environments where teachers may share knowledge and resources related to AI (Zawacki-Richter et al., 2021). However, although self-efficacy is generally looked upon as a positive motivator, Kin et al. (2020) claim that over-confidence can result in misconceptions about one's ability to utilize technology effectively, which can result in negative consequences if not managed appropriately.

The research findings on the effect of AI literacy on teachers' adoption intentions (H5) indicate that AI literacy has a strong positive impact on PSEFLTs' adoption intention. The knowledge of AI is, therefore, a key factor that determines teachers' intention to try AI in their classes, in that it encompasses the knowledge and skills needed to understand, evaluate, and use the AI technologies in educational environments (Ayanwale, 2022). In particular, those teachers who have a proper understanding of AI would appreciate the advantages that these tools bring, such as personalized learning experiences and the active participation of learners (Holmes & Tuomi, 2022). Studies have highlighted that teachers with higher AI literacy tend to adopt a combination of AI tools and creative teaching methods. This is because they feel more confident in handling complex technologies (Zawacki-Richter et al., 2021). Additionally, it is AI literacy that enables educators to evaluate the ethical outcomes of AI use in teaching, thereby cultivating a more responsible technology approach (Deng, 2024). Consequently, the development of AI literacy through training programs is imperative for supporting pre-service and in-service teachers and enhancing their willingness to integrate AI in their educational practice. By imparting PSEFLTs with critical information skills, schools can enable a smoother transition towards AI technology integration, benefitting both students and teachers (Lee & Perret, 2022; Sanusi et al., 2021). The positive association between AI literacy and PSEFLTs' behavioral intention to implement AI is supported by a study conducted by Lin et al. (2025), in which a deeper understanding of AI constructs strengthens teachers' intention to use AI tools in educational settings. In a similar study conducted on 545 school students in China, Chai et al. (2020) discovered that contextual factors, such as AI literacy, positively contribute to learning intention. Long and Magerko (2020) emphasized that AI literacy enables teachers to assess AI tools in a critical manner, and therefore, become more inclined towards AI technology integration and its effective use.

Concerning AI readiness and PSEFLTs' behavioral intention (H6), the findings derived in this study contribute immensely to current literature. It was found that AI readiness is a critical factor in shaping teachers' intention to use AI in educational settings, as it reflects their preparedness and willingness to effectively integrate AI technologies (Ayanwale et al., 2022; Trotsko et al., 2019; Zawacki-Richter et al., 2021). Teachers' use of AI tools is more likely when they view themselves as ready enough to work with such technology, seeing them as useful tools for enhancing instruction and student achievement (Zawacki-Richter et al., 2021). Readiness for AI integration is shaped by various factors, including access to professional training, familiarity with AI concepts, and the availability of supportive resources (Lee & Perret, 2022). Research suggests that teachers who perceive themselves as adequately ready exhibit greater confidence in navigating the complexities of AI applications. This readiness, in turn, fosters a more positive disposition toward the adoption and implementation of AI technologies in educational settings (Ayanwale et al., 2024). The study's confirmation of a positive relationship between AI readiness and behavioral intention supports findings by Ayanwale et al. (2022), Damerji and Salimi (2021) and Jatileni et al., (2024).

While this study is grounded in the Iranian educational context, the findings have potential international relevance. The constructs examined, AI self-efficacy, AI literacy, AI readiness, perceived usefulness, and perceived ease of use, are foundational components of the widely used Technology Acceptance Model (TAM), which has been validated across diverse cultural and institutional settings. The strong predictive power of these variables in shaping pre-service teachers' behavioral intentions suggests that similar trends may emerge in other educational systems facing the global push toward AI integration. Moreover, comparative studies (e.g., Ayanwale et al., 2024; Lu et al., 2024) conducted in countries like South Africa and China have reported parallel findings regarding the role of AI literacy and self-efficacy, underscoring the generalizability of these results. Therefore, although local factors may mediate the degree of adoption, the conceptual framework and implications of this research are likely to resonate beyond the Iranian context, offering valuable insights for teacher education programs worldwide.

Conclusion

This study sheds light on the key factors that influence PSEFLTs' behavioral intention to incorporate AI into their future classrooms. It highlights the importance of aspects like self-efficacy, perceived usefulness, ease of use, AI literacy, and readiness. Out of the tested six hypotheses, five were supported. The positive effects of perceived usefulness, perceived ease of use, AI self-efficacy, AI literacy, and readiness on PSEFLTs' behavioral intention were significant. This research thus contributes to the understanding of technology adoption in the realm of education from the perspective of TAM. Factors such as AI readiness or literacy expand the perspective of TAM and aptly explore the unique challenges and opportunities for integration into education presented by AI.

Theoretical and Practical Implications

From a practical standpoint, the results highlight the necessity of focused professional development courses that give PSEFLTs the skills and assurance they need to use AI tools efficiently. Teacher education programs should focus on enhancing AI literacy and readiness through supportive and interactive training modules. Providing access to recourses such as user-friendly AI tools, practical demonstrations, and collaborative learning opportunities can help future educators build confidence in their ability to incorporate AI into their lesson plans.

Policymakers and school administrators should prioritize creating an environment that supports AI integration, including infrastructure investment, technical support, and institutional encouragement. Additionally, efforts to foster a culture of innovation and acceptance among educators can facilitate smoother adoption and promote the effective use of AI to improve teaching and learning.

By addressing both theoretical and practical aspects, this study offers actionable insights that pave the way for a more effective and inclusive integration of AI technologies in educational systems, ultimately contributing to the development of a future-ready teaching workforce.

Limitations of the Study

Despite its contributions, this study has several limitations that must be acknowledged. First, the sample was limited to 100 Iranian pre-service English language teachers from three teacher education universities, selected through convenience sampling. As such, the findings may not be generalizable to pre-service teachers in other cultural, institutional, or disciplinary contexts. Differences in teacher training curricula, access to educational technologies, and cultural perceptions of AI may significantly influence attitudes and behavioral intentions in other countries.

Second, the study relied exclusively on self-reported data, which may be influenced by social desirability bias or participants' limited introspective accuracy. Respondents might have overestimated their AI readiness or minimized their anxiety levels, potentially skewing the results.

Third, the use of a cross-sectional design restricts the ability to establish causal relationships among the variables. Behavioral intention is a dynamic construct that may evolve over time, particularly as pre-service teachers gain more exposure to AI tools or receive targeted training.

To address these limitations, future research should consider employing longitudinal designs to observe changes in behavioral intentions over time. Additionally, mixed-methods approaches that incorporate qualitative interviews or classroom observations could provide a more nuanced understanding of how pre-service teachers engage with AI in authentic contexts. Comparative studies across different countries or educational systems would also be valuable to explore the extent to which cultural, infrastructural, or pedagogical factors moderate the relationships identified in this study. Such research could offer a more globally informed framework for integrating AI into teacher education programs.

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Conflict of Interest

The authors declare no conflict of interest.

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