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Pre Service Teachers' Acceptance, Readiness and Intention to use Artificial Intelligence in Teaching English- Scale Development and Validation

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Abstract: This study developed and validated a scale to measure pre-service teachers' acceptance, readiness, and intention to use Artificial Intelligence (AI) in teaching English. The scale was grounded in three complementary theoretical frameworks: the Unified Theory of Acceptance and Use of Technology (UTAUT) for acceptance, Social Cognitive Theory (SCT) and Constructivist Learning Theory for readiness, and the Theory of Planned Behavior (TPB) for intention. An initial pool of 35 items was generated from established theories and relevant literature. Following face and content validation by six experts, two items were removed based on the Content Validity Index, resulting in a 33-item draft instrument. The scale was then administered to 652 pre-service teachers enrolled in B.Ed. and M.Ed. programmes across six states in India. Item purification led to the deletion of two additional items, producing a final 31-item scale. Exploratory Factor Analysis on one half of the sample and Confirmatory Factor Analysis on the other half supported a clear three-factor structure comprising acceptance, readiness, and intention. The model demonstrated satisfactory psychometric properties, including strong factor loadings, substantial explained variance, acceptable model fit indices, and high internal consistency reliability (overall Cronbach's alpha = 0.915). The validated scale offers a comprehensive and reliable instrument for assessing how future teachers perceive and prepare for AI integration in English language teaching. It also provides a useful basis for teacher education institutions, curriculum designers, and policymakers to identify training needs and design targeted interventions for meaningful AI integration in language education.

Keywords: Artificial Intelligence, English, India, Pre-Service Teachers, Scale Development, Validation.

1. Introduction

Established in 2015, the Sustainable Development Goals (SDGs) of United Nations (UN) layout a roadmap for achieving a more promising and sustainable future for all (Opoku, 2016). Specifically, SDG 4 is concerned with ensuring that everyone has access to excellent and inclusive education that promotes opportunities for lifelong learning (Unterhalter, 2019). Despite tremendous advancements in accessibility, there are countless challenges to overcome (Patidar, 2025; Saifulla *et al.,* 2024). Approximately 262 million children and adolescents are still not enrolled in school, and many of those who are enrolled do not fulfil the basic competency standards in important areas like reading and maths, according to recent reports (Saini *et al.,* 2023). Geographical barriers, systemic disadvantages, and socioeconomic variables frequently make these discrepancies worse, underscoring the urgent need for targeted efforts to guarantee that no one finds themselves left behind (Gale *et al.,* 2022; UNESCO, 2018). By integrating technology, education can be made more accessible and engaging, thus filling this gap.

Artificial intelligence (AI) is a computer system and algorithm that can handle novel situations, carry out intricate activities, and resolve issues that crop up (Castillo-Girones *et al.,* 2025; Coppin, 2004). It possesses the possibility to completely transmute education by addressing systemic issues with educational access, quality, and equity in addition to automating administrative work and personalizing learning experiences (Chou *et al.,* 2022). Generative AI and LLMs have shown incredible potential in revolutionizing educational methods (Han, 2024; Rashid *et al.,* 2024; Zirar, 2023). Martinez (2019) described AI as an autonomous system, software, program, or algorithm that can make judgments, think and act logically, enact humanely, and produce results. Its primary applications are personalized learning (Vandewaetere & Clarebout, 2014) and adaptive learning (Zhang & Zhang, 2020). AI also offers content recommendations for learners based on an assessment of their interest overtime, promoting exploration and in-depth learning (Garzón *et al.,* 2025; Tomić *et al.,* 2022). Speaking in line of language learning, AI tools teach correct pronunciations and comprehensions of words and sentences through real-time feedback. It grades and assesses within fractions of sections, providing faster, objective feedback to students and thus, allows educators to hold meaningful discussions (Cope *et al.,* 2021; Mota & Martins, 2023). Furthermore, when educators decide to incorporate augmented reality (AR) and virtual reality (VR), a highly indulging and participatory learning environment can be created (Al-Ansi *et al*., 2023; Bailey, 2019; Choudhury *et al.,* 2024; Choudhury & Chechi, 2024). It also improves accessibility for disable and special needs students. On the whole, we notice AI playing an efficient, inclusive and personalized role in reshaping education.

Having mapped out the possible advantages and uses of AI in education, it comes down to the pre-service teachers for its successful execution in their pedagogy as they take up a vital role in the future. One of the determining factors is the teachers' acceptance of AI tools for its successful incorporation in their pedagogy. Ausserer and Risser (2005) described it as a phenomena that indicates the degree of willingness of potential consumers to utilize a particular system. According to Venkatesh *et al.* (2003), Theory of Acceptance and Use of Technology (UTAUT) state that pre-service teachers, being at the threshold of their professional journeys, need a positive view of AI being a valuable addition in their teaching toolkit. A study in 2023 discovered that pre-service teachers' acceptance of AI tools such as language learning platforms, significantly enhanced their intention to use it in their pedagogical practices (Zhang *et al.,* 2023). On the whole, we see that without acceptance, even well-developed highly beneficial AI tools will be resisted. Parasuraman (2000) outlined technology readiness as people's inclination to accept and employ new technology in order to accomplish objectives. This encompasses understanding of the functionalities, having technical skills and confidence in using AI tools effectively. Wing *et al,* (2025) disclosed that teachers who felt prepared and ready were more likely to experiment with AI tools, which led to innovative teaching practices that catered to diversity among the needs of the students. As for Intention- condition in which the individual or agent is intended to act (Raz, 2017), Yao and Wang (2024) concluded that pre-service educators who hold a strong intention were more likely to convert their acceptance and readiness into action.

While the benefits of AI in teaching in general and specifically teaching English language are documented, it depends on the pre-service educators' acceptance, readiness and intention to incorporate it in the future as they begin their career. The development of a scale that assesses these three aspects among pre-service teachers will address a significant gap in literature, since no existing tool comprehensively measures all the three as per the knowledge of the investigators. This wholesome scale is also crucial to offer actionable insights for teacher training programs and also for education policy makers to design tailored interventions. Though the samples are limited to pre-service teachers in India, the scale is well established on three widely validated theoretical frameworks. The three constructs of acceptance, readiness and intention are not culturally bound to India. Thus, its conceptual relevance across international and multicultural contexts when adapted and revalidated is enhanced. Aim of this study is to develop and validate a comprehensive scale that assesses pre-service teachers' acceptance, readiness and intention to use artificial intelligence (AI) tools to teach English.

2. Review of Literature

2.1 Significance of AI in English Language Teaching

The use of AI-powered tools in the acquisition of English language has been studied by numerous authors, as demonstrated by Alsadoon (2021), Alharbi (2023), Alhalangy and AbdAlgane (2023) and Dewantara *et al.,* (2024). Several studies show that using AI tools in teaching non-native language increases students' academic achievement (Khan *et al.,* 2021; Kim, 2021), motivation (Moybeka *et al.,* 2023), and engagement. With regards to teachers, according to Amin's (2023) research, they may better fulfill the needs of each individual student with ChatGPT's tailored real-time language practice, learning experiences and lesson planning support. As for language learning in particular, using AI tools into English language instruction improves students' speaking, writing, listening, and reading abilities (Adilbayeva *et al.,* 2022). The usage of chatbots with English language learners at the undergraduate level was investigated by Annamalai *et al.* (2023). According to the study, chatbots can help learners become more competent and autonomous. Kazu and Kuvvetli (2023) created a pronunciation model for Turkish learners that was backed by AI. Longer vocabulary retention and notable gains in acquiring consonant and vowel sounds were the outcomes of that approach.

2.2 Existing Tools on AI as an Educational Technology – Research Gap

Several studies have developed and validated instruments to measure each of these three aspects among teachers. Zhang *et al.* (2023) undertook a multigroup analysis study among pre-service educators and examined their acceptance of AI. Likewise, Alejandro *et al.* (2024) elicited pre-service educators AI technology acceptance which linked their attitudes to factors such as their exposure during training to AI tools. Guo *et al.* (2024) also validated an instrument to examine in-service teachers AI acceptance while throwing light on the diverse educational contexts. Ramazanoglu and Akın (2024) also focused on developing a robust scale to assess AI readiness among in-service teachers. Chai *et al.* (2024) undertook a survey that measured various factors that determine students' intentions to learn about AI. Among the existing scale, the most thorough study that specifically assessed three factors- AI literacy, readiness-confidence, and acceptability among pre-service teachers seems to be the scale created by Keir A. Balasa (2025). We conclude that while all of this research endeavors have developed tools to gauge each of the three components under scrutiny independently, none have gauged all three components together. Further, only one of the study gauged three components but are not the same as we intended to. This is the research gap that we aimed to fill and conceptualize these three components as related yet independent constructs.

2.3 Adoption of Theories

The development of the scale was firmly grounded in well-established theoretical frameworks. Each construct (i.e. acceptance, readiness and intention) was led by relevant theories which provided robust foundations. Acceptance (A) component was designed based on Venkatesh *et al.* (2003)'s Unified Theory of Acceptance and Use of Technology (UTAUT) model. The four key dimensions were accepted and relevant items were pooled. As for the readiness (R) component, two different theories i.e. Social cognitive theory (SCT) and Constructivist learning theory formed the theoretical background. Additionally, Ribble's (2008) dimensions and ethical perspectives of Floridi and Taddeo (2016) gave broader insights for this component. Finally, intention (I) component was based on Theory of planned behavior (TPB). Since subjective norm in TPB gathered similar information to social influence in UTAUT model, it was excluded to avoid overlapping. Items across three components were either completely adopted or inspired from research articles.

The theories are selectively integrated and constructs redefined to develop a more context-specific scale that is specific to AI use in teaching English language. Further, the two overlapping dimensions were streamlined to avoid duplication and enhance conceptual clarity.

2.4 Conceptual Framework

Operational definition of the three constructs in the context of the study is as follow: *Acceptance* is the pre-service teachers favorable and positive view of AI being a useful and easy to use tool for teaching English. *Readiness* is the pre-service teacher's preparedness to actually integrate AI into their English teaching pedagogy. It captures their knowledge, skill and confidence. *Intention* is the pre-service teacher's likelihood of incorporating AI tools into future English teaching practice. Figure 1 displays the conceptual framework across three constructs.

Acceptance is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh *et al.,* 2003) which explains that when pre-service teachers perceive AI as enriching their teaching performance (performance expectancy), requiring acceptable level of effort (effort expectancy), endorsed by peers and colleagues (social influence), and supported by institutional infrastructure (facilitating conditions), they form acceptance of AI. This acceptance then drives readiness i.e., teachers who have already evaluated AI as favorably and positive are motivated to build the competencies/skills needed to use it. Readiness is theoretically anchored in Social Cognitive Theory (SCT; Bandura, 1986) and Constructivist Learning Theory (Vygotsky, 1978). The pre-service teachers who have developed knowledge and skills of AI tools build self-efficacy which is central here. Constructivist learning theory complements this by explaining how readiness develops i.e., active exploration, collaborative knowledge construction, etc. Eventually, ready teachers then form strong intentions to use AI because SCT predicts that self-efficacy directly influences behavioral intention. Another link is via Theory of Planned Behavior as it predicts that even with favorable and positive attitudes (i.e. acceptance), intention will remain weak if perceived behavioral control is low. Thus, readiness serves as the proximal, enabling predictor of intention as it transforms favorable attitudes into actionable plans. Thus, these concepts show an interconnected relationship in which behavioral intention is shaped by preparedness (i.e. readiness), which in turn is influenced by acceptance.

UTAUT guided acceptance item generation around its four determinants, while SCT and constructivist theory shaped readiness items, and TPB directed intention items. The items generated under each construct justified sampling pre-service English teachers specifically. For EFA/CFA, the four theories predicted a three-factor correlated structure (rotation in EFA and three-factor CFA model), and discriminant validity testing verified that the theoretically distinct constructs were also empirically separable.

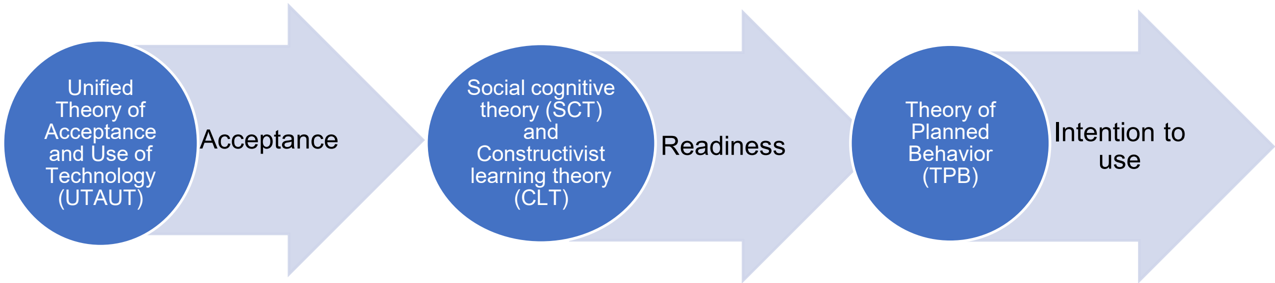

Figure 1. Conceptual framework showcasing three constructs

3. Materials and Methods

3.1 Scale Development

Phase 1: Item Generation and Designing the Draft Scale

The most representative theories and dimensions of these three components were located as the first step. The dimensions were identified and selected based on the theories mentioned earlier and then by referring to research articles published in reputed journals (Yilmaz, Yilmaz, and Ceylan 2023; Anh, Phong, and Jan, 2023; Gümüşoğlu and Akay 2017; Venkatesh et al., 2003; Bandura, 1997; Ramazanoglu and Akın, 2024; Bawa and Zubairu, 2015; Kalpana, 2014; Ribble, 2008; Floridi and Taddeo, 2016; Compeau and Higgins, 1995; Teo and Lee, 2010.; Davis, 1989; Bidin *et al.,* 2011; Chai *et al.,* 2021). The initial AI acceptance, readiness and intention questionnaire with 35 items and 10 dimensions was formulated, including *acceptance* with 13 items (Subscales: 1. Performance expectancy- A1, A2, A3, A4; 2. Effort expectancy- A5, A6, A7; 3. Facilitating conditions- A8, A9, A10; 4. Social influence- A11, A12, A13). *readiness* with 12 items (Subscales: 1. Technology self-efficacy- R14, 15, R16, R17; 2. Student interaction- R18, R19, R20, R21; 3. Ethical awareness- R22, R23, R24, R25), and *intention* with 10 items (Subscales: 1. Attitudes towards usage- I26, I27, I28, I29; 2. Perceived behavioural control- I30, I31, I32; 3. Behavioural intention to use- I33, I34, I35). All the three aspects of the scale were gauged on a Likert scale with five-point (1=strongly disagree to 5=strongly agree).

Once the initial scale was developed, two English language experts were referred and the precision of the language used across the 35 items was confirmed. Further, a panel of six subject experts i.e. Professors from different

Universities were chosen to determine the face and content validity of the draft scale. They were requested to rate the items based on question clarity, accuracy, relevance and also interpretability using a Likert rating scale with four-points (1= Not relevant to 4= Highly relevant). The most vital and correct content in the instrument maintains the confidence of its validity. Additionally, the panel assisted in determining and assessing the content validity of the items that were first chosen for the questionnaire.

Phase 2: CVI Calculation

The CVI method was employed to elicit the experts' perceptions about the content validity of the scale which can be examined by item-level CVI (I-CVI) and scale-level CVI (S-CVI) methods (Ayre & Scally, 2014; Zamanzadeh *et al.,* 2015). The S-CVI/average of 0.9 is indicative of an excellent content validity; whereas, I-CVI values of at least 0.83 from six experts is acceptable (Lynn, 1986). Here, the S-CVI/average was 0.952 and I-CVI of two items were less than 0.83 and thus were deleted (Items 20 & 25- *readiness* dimension). Thus, the final number of items was 33, and spread across the three dimensions.

3.2 Research Design, Samples and Data Collection Process

A non-experimental descriptive research design, based on quantitative data collection was carried out among pre-service teachers pursuing B.Ed or M.Ed programs across six states in India. This research design is appropriate for eliciting the current state of *acceptance, readiness and intention* towards AI usage for teaching English. A total of 652 pre-service teachers from 10 colleges in West Bengal, five colleges each in Odisha, Jharkhand, Assam and Maharashtra, and four colleges in Uttar Pradesh were chosen randomly by email invitations in the mid of 2024. This ensured representation from different cultural contexts and geographical settings. Those who were willing to take part voluntarily were encouraged to respond to the best of their honesty, ranking each item on a five-point Likert scale.

3.3 Data Analysis

The completed questionnaires were decoded and checked for missing values, errors and outliers before the application of statistical procedures using IBM SPSS v29 and AMOS v26 to analyze the data. As the first step, the 652 samples were divided into two equal halves (EFA= 326 and CFA= 326) randomly. The scale with 33 items was analyzed by Churchill's item purification method (Churchill, 1979) where the original five-point Likert scale format was retained. Following that, Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of Sphericity (BTS) were performed prior to determine the sample appropriateness for factor analysis. Sequentially, the randomly divided first independent group (n=326) to perform EFA was achieved through PCA with varimax with rotation method. Additionally, CFA was used to verify compatibility on the second half of the sample (n=326). Finally, the reliability was determined by measuring its internal consistency using Cronbach's alpha coefficient for each of its dimension and as a whole.

4. Results

4.1 Demographic Profile

The table 1 presents the basic demographic profile and technology-related characteristics of the participants. In terms of gender, the sample is male dominated i.e., out of the total respondents, 399 (61.2 percent) are males, while 253 participants (38.8 percent) are females. With respect to digital literacy levels, the participants are fairly evenly distributed across the three categories. About one-third of the respondents (32.8 percent; n = 214) reported that they always demonstrate digital literacy, while 34.2 percent (n = 223) indicated that they often possess digital literacy skills, and the remaining 33 percent (n = 215) reported never having adequate digital literacy. This distribution suggests almost even distribution in digital literacy levels among the participants without a single category dominating.

Table 1. Demographic Profile and Technology-related Characteristics

Variable	Categories	N	%
Gender	Male	399	61.2
	Female	253	38.8
Digital literacy levels	Always	214	32.8
	Often	223	34.2
	Never	215	33
Prior AI exposure limits	Yes	331	50.8
	No	321	49.2

Regarding prior AI exposure limits, slightly more than half of the respondents (50.8 percent; n = 331) reported having some form of prior exposure to AI, whereas 49.2 percent (n = 321) indicated no prior exposure. This near-equal split reflects a balanced representation of participants with and without previous exposure to AI tools.

4.1.1 Purification

The corrected item-total correlation statistics were analyzed and those less than or equal to 0.3 were considered insignificant and are recommended to be deleted (DeVellis & Thorpe, 2021). Therefore, two items i.e. item no.8 of *acceptance* (0.037) and item no. 27 of *intention* (0.239) were deleted because they did not satisfy the suggested minimum factor loading of 0.4 and were negligible contributors to the factor structure (Howard, 2016).

4.2 Exploratory Factor Analysis (EFA)

4.2.1 Suitability of Data

EFA is a statistical technique for figuring out a large set of variables' underlying structure. In essence, its purpose is to decrease the quantity of variables into fewer ones in order to simplify complex data which sets the basis for structural equation modelling (Costello & Osborne, 2019; Hair *et al.,* 2010). EFA was conducted on the respondents acceptance, readiness and intention to use AI tools in teaching English construct using IBM SPSS v29 with a sample of 326 on the retained 31 items. Determining whether the data is suitable for analysis is crucial to ensuring the validity of the EFA (Conway & Huffcutt, 2003). Therefore, the two following tests (Table 2) were conducted:

Table 2. KMO and Bartlett's Test of Sphericity

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.862
Bartlett's Test of Sphericity	Approx. Chi-Square	17666.748
	Df	465
	Sig.	.000

I. KMO Sampling Adequacy Measure: The obtained value was 0.862 and it is considered excellent for factor analysis as it is well above 0.60 threshold (Awang, 2012).

II. Bartlett's test for sphericity: BTS was statistically significant, $\chi^2(465) = 17666.748$, $p < .001$. This shows that the correlation matrix was not identical and proved the data to be suitable for factor analysis.

4.2.2 Total Variance

Additionally, there are three methods to ascertain the number of components required to measure a construct in a questionnaire: the scree plot, a cumulative variance greater than 60%, or an eigenvalue greater than 1. The total variance explained for the construct was determined and it demonstrated that all the three components have eigenvalues larger than 1. Component 1 accounted for 29.217% of the variation, followed by Component 2 at 26.926%, and Component 3 at 22.3777%. The overall variance explained by this concept was 78.520%. Therefore, the total variance explained was sufficient because it was higher than the 60% minimum criteria.

4.2.3 Rotated Component Matrix

As the subsequent step, EFA was analyzed for eliciting underlying factor structure. Items with factor loadings less than 0.5 (Kaiser, 1960), items with similar loadings on two factors, items that were incorrectly classified based on specific conceptual factors, and items that are removed and EFA repeated until a more distinct factor structure appears are the principles that guide item selection in EFA (Ferguson & Cox, 1993; Costello & Osborne, 2019). The factor loadings as seen in Table 3, 4 and 5 ranged between .989 ≥ λ ≥ .727, which are all ≥ .50 and is considered appropriate (Hair *et al.,* 2006). In fact, we noticed that each item loadings were greater than 0.70, which is indicative of an excellent construct validity (Hair *et al.*, 2010). Also, there were no significant cross-loadings, implying a strong discriminant validity. Thus, all 31 items across three dimensions were retained (*acceptance a*= 12 items; *readiness r*= 10 items and *intention i*= 9 items) and included to the construct underlying the factor.

Table 3. Rotated Component Matrix of Factor 1: Acceptance
Extraction Method: Principal Component Analysis
Rotation Method: Varimax with Kaiser Normalization

Item Code	Item	Component		
		1	2	3
A10	I can reach out to a person/group for assistance with AI difficulties	0.920		
A11	People important to me think that I should use AI applications	0.915		
A7	AI applications are compatible with other technologies I use	0.914		
A2	AI usage will better my English teaching quality	0.911		
A12	People who influence my behaviour think I should use AI applications	0.906		
A4	AI usage enables me to accomplish teaching tasks more quickly	0.893		
A5	Learning how to use AI applications is easy for me	0.887		
A13	People whose opinions I value refer me to use AI applications	0.881		
A1	I find AI applications useful in my daily life	0.861		
A6	AI applications are easy to use	0.789		
A8	It is easy for me to become skilful at using AI applications	0.760		
A3	AI usage will increase my productivity in teaching English	0.727		

Table 4. Rotated Component Matrix of Factor 2: Intention

Item Code	Item	Component		
		1	2	3
I32	I will continue to acquire AI-related information		0.989	
I33	I will keep myself updated with the latest AI applications		0.984	
I25	Working with AI is fun		0.982	
I30	My interaction with AI applications is clear and understandable		0.974	
I28	I find it easy to get AI to do what I want it to do		0.972	
I31	I will use AI in my profession in future		0.970	
I29	Using AI to teach the course content is entirely within my control		0.960	
I24	AI applications make work more interesting		0.943	
I26	I like using AI for teaching English		0.857	

Table 5. Rotated Component Matrix of Factor 3: Readiness

Item Code	Item	Component		
		1	2	3
R22	I exhibit ethical behaviour in the use of AI applications			0.865
R21	I am aware of my ethical responsibilities in AI applications			0.863
R23	I can detect unethical AI practices			0.858
R20	I can mentor students for AI projects			0.853
R18	I can lead classroom discussions on AI topics with students			0.832
R14	I can solve the technical problems of AI applications			0.815
R17	I can analyze data generated by AI tools to assess student progress			0.811
R16	I can manage AI projects in the classroom			0.808
R15	I can develop AI projects to teach English			0.807
R19	I can design activities that encourage student interaction regarding AI			0.785

4.2.3 Confirmatory Factor Analysis (CFA)

CFA checks the convergent and discriminant validity of the construct under scrutiny. Figure 2 displays the standardized loadings of all the 31 items to range from 0.92 to 0.68. Thus, every value was determined to be significant (p <0.05). As a result, no item had to be removed since a good validity was obtained.

After which, the three dimensions with 31 items were examined for model fit indices. According to Table 6, the similarity ratio was calculated to be P<0.01; the ratio of chi-square statistics to degrees of freedom was calculated as (X^2 /df) =1.457 (i.e. between 1 and 3). The root mean square error of approximation was calculated as (RMSEA)=0.037 (i.e. <0.06); root mean square residual (RMR) was calculated as=0.023 (<0.08); comparative fit index (CFI) was calculated as= 0.972 (i.e. >0.95); goodness of fit index (GFI) was calculated as= 0.887 (<0.9); adjusted goodness of fit index (AGFI)= 0.871. All fit indices met the threshold values mentioned in the brackets (Ding & Ng, 2008). Thus, the structural validity of the three dimensional 31-items scale was accepted.

Table 6. The Fitness Estimates of the Model

Measures	Estimate
P value	0.000
Minimum Discrepancy Function by Degrees of Freedom divided (CMIN/DF)	1.457
Root Mean Square Residual (RMR)	0.023
Root Mean Square Error of Approximation (RMSEA)	0.037
Goodness of Fit index (GFI)	0.887
Adjusted Goodness of Fit Index (AGFI)	0.871
Comparative Fit Index (CFI)	0.972

4.2.4 Reliability Analysis

Values in internal consistency reliability above 0.70 are deliberated as acceptable, above 0.80 as good, whereas above 0.90 as excellent (Table 7) (DeVellis, 2003; Nunnally & Bernstein, 1994). Thus, the values here are considered to be excellent (Nunnally & Bernstein, 1994). The *acceptance (A)* dimension yielded an internal consistency of 0.970 for 12 items, *readiness (R)* dimension yielded 0.950 for 10 items and *intention (I)* dimension yielded 0.990 for 9 items. Likewise, for the whole scale with 31 items and three dimensions, the Cronbach's alpha is 0.915.

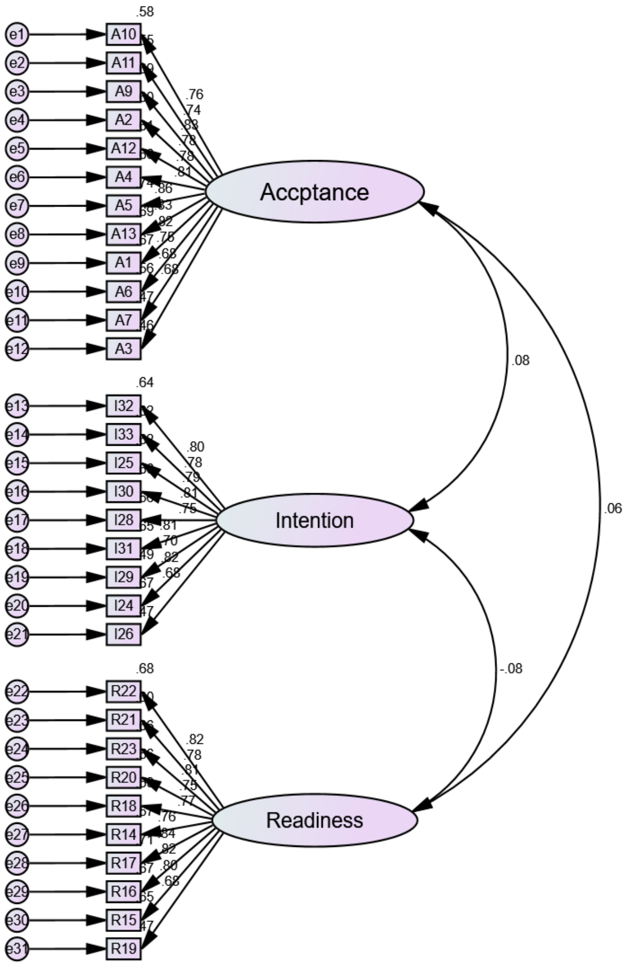

Figure 2. The Factor Structure of the Model with 31 items of Pre-Service Teachers Acceptance, Intention and Readiness to Use AI In Teaching English Scale

Table 7. Reliability Quotients

Dimensions	No. of Items	Cronbach's Alpha
Acceptance (A)	12	0.970
Readiness (R)	10	0.950
Intention (I)	9	0.990
Overall	31	0.915

5. Discussion

The findings of the present study provide strong evidence that the proposed instrument is psychometrically sound and conceptually meaningful for assessing pre-service teachers' acceptance, readiness, and intention to use AI in teaching English. The scale development process followed a logical sequence from theory-based item generation to expert validation, purification, and factor validation. Starting from 35 items and reducing the pool to 31 after content validation and item-total correlation analysis reflects a careful refinement process rather than arbitrary item removal. This strengthens confidence that the final items are not only statistically adequate but also relevant to the intended constructs. The high S-CVI/average value and the removal of weak items at successive stages suggest that the final instrument achieved both content precision and empirical coherence.

The EFA results support the structural robustness of the scale. The KMO value of 0.862 and the significant Bartlett's test indicate that the data were well suited for factor analysis. More importantly, the three extracted components explained 78.520% of the total variance, which is notably high for a newly developed educational scale. Such a level of explained variance indicates that the retained factors account for a substantial proportion of participant responses and that the construct is captured efficiently by the final item set. In addition, the factor loadings ranged from 0.727 to 0.989, with no meaningful cross-loadings, showing that the items clustered strongly under their intended dimensions. This is important because the study did not merely seek to measure a general positive attitude toward AI; it aimed to distinguish among acceptance, readiness, and intention as related but separate constructs. The EFA findings support that distinction clearly. The CFA findings further strengthen the argument for structural validity. The reported standardized loadings, together with the fit indices, indicate that the three-factor model provides an acceptable representation of the observed data. The values for RMSEA, RMR, CFI, and the chi-square to degree-of-freedom ratio particularly suggest a well-fitting model. This means that the conceptual structure proposed in the study was not only theoretically reasoned but also empirically supported. In practical terms, the CFA confirms that acceptance, readiness, and intention are distinguishable dimensions that work together within a broader framework of AI integration preparedness among pre-service English teachers. The validation of this three-dimensional structure is one of the most important contributions of the study because it offers a more holistic framework than many earlier tools that focused on only one of these constructs in isolation (Zhang *et al.,* 2023; Ramazanoglu & Akın, 2024).

Another major strength of the study lies in its theoretical integration. Acceptance was anchored in UTAUT, readiness in SCT and Constructivist Learning Theory, and intention in TPB. This combination is meaningful because AI integration in teaching is not driven by a single psychological or technological factor. Pre-service teachers may recognize the usefulness of AI, but that recognition alone does not ensure pedagogical preparedness. Likewise, feeling prepared does not automatically translate into implementation unless the individual also has a clear behavioural intention. By connecting these three constructs in one instrument, the study reflects the actual process through which future teachers are likely to move from perception to preparedness and then to intended practice. The conceptual framework therefore adds value to the literature by organizing AI-related teacher preparedness in a sequential and educationally relevant manner. The strong reliability coefficients also deserve close attention. The overall Cronbach's alpha of 0.915 indicates excellent internal consistency, while the subscale alphas for acceptance, readiness, and intention are also very high. These findings suggest that the items within each dimension function coherently and measure the same underlying attribute. For scale users, this is particularly important because it means the instrument can be used with confidence in similar teacher education settings. At the same time, the high reliabilities support the claim that the scale may serve as a stable baseline tool for diagnosis, programme evaluation, and future comparative studies. In the context of AI in education, where many instruments are still emerging and often domain-general, a reliable, context-specific tool focused on English language teaching is a valuable addition (Cope *et al.,* 2021; Zhang *et al.,* 2023).

The study also has clear practical implications. Since the instrument measures three distinct aspects of AI integration, it allows teacher education institutions to identify where support is most needed. For example, low acceptance scores may point to concerns about usefulness, effort, or institutional support. Low readiness scores may indicate inadequate skills, confidence, or ethical awareness. Low intention scores may suggest that even when trainees appreciate AI and possess some competence, they may still hesitate to apply it in future teaching. This diagnostic potential makes the scale relevant not only for research but also for curriculum design, teacher preparation modules, and institutional planning. In particular, B.Ed. and M.Ed. programmes can use the scale to design targeted interventions that go beyond general digital literacy and focus specifically on pedagogically meaningful AI use in English teaching. The study further gains importance from its disciplinary focus. AI adoption in education is often discussed in broad terms, yet the demands of English language teaching are distinctive. AI tools can support pronunciation practice, adaptive feedback, writing assistance, conversational interaction, and personalized learning paths, all of which are especially relevant in language education. By developing a scale specifically for teaching English, the study recognizes that the pedagogical meaning of AI is shaped by subject context. This subject-specific orientation strengthens the instrument's educational relevance and differentiates it from more generic technology acceptance measures. It also positions the study within an important area of current educational transformation where language teaching is increasingly influenced by AI-enabled tools (Annamalai *et al.,* 2023; Cope *et al.,* 2021).

At the same time, the findings should be interpreted with caution. The sample, although large and geographically diverse within India, remains limited to one national context and to pre-service teachers in English teaching programmes. Therefore, the scale cannot yet be assumed to function identically across cultures, subjects, or professional stages. In addition, the study used a cross-sectional survey design, which means the scale's stability over time was not tested. It is also based entirely on self-reported responses, which may be affected by social desirability or inflated self-perceptions regarding AI competence and willingness. These limitations do not weaken the value of the current validation, but they do indicate that the instrument should undergo further cross-validation, longitudinal testing, and possible adaptation in other settings before broader generalization is claimed.

Overall, the study makes a meaningful contribution by offering a theoretically grounded, empirically validated, and context-specific instrument for understanding how pre-service teachers relate to AI in English language teaching. Its main contribution lies not simply in producing another scale, but in integrating three closely connected dimensions that together reflect preparedness for future pedagogical use of AI. The results suggest that the instrument can support both scholarly inquiry and institutional decision-making. Future work should now move toward replication in other regions, testing with in-service teachers and teacher educators, and examining how scores on these three dimensions relate to actual classroom practice and professional development outcomes. Such extensions would further establish the scale as a significant tool in the evolving field of AI-enabled teacher education (Ramazanoglu & Akın, 2024; Zhang *et al.,* 2023).

5. Conclusion

The present study successfully developed and validated a comprehensive scale to assess pre-service teachers' acceptance, readiness, and intention to use Artificial Intelligence in teaching English. Beginning with a 35-item draft grounded in UTAUT, Social Cognitive Theory, Constructivist Learning Theory, and the Theory of Planned Behavior, the instrument was refined through expert review, content validity assessment, item purification, and factor analytic procedures. The final scale consisted of 31 items distributed across three conceptually distinct yet interrelated dimensions: acceptance, readiness, and intention. Findings from both Exploratory Factor Analysis and Confirmatory Factor Analysis confirmed the structural soundness of the instrument, while the reliability coefficients demonstrated strong internal consistency for each dimension as well as for the overall scale. The validated tool contributes to the growing literature on AI in education by addressing a clear gap: the absence of an integrated scale focused specifically on pre-service teachers and English language teaching. Its value lies not only in measuring perceptions, preparedness, and future use intention, but also in helping teacher education institutions identify the areas in which support is most needed. The scale may therefore serve as a practical diagnostic instrument for curriculum planning, professional preparation, and policy design related to AI-enabled pedagogy. At the same time, the study should be interpreted in light of its contextual limitations, including its cross-sectional design, reliance on self-report data, and focus on Indian pre-service teachers in English teaching contexts. Future studies may extend its application across countries, subject areas, and teacher populations, and may also examine its longitudinal stability. Overall, the scale provides a strong empirical foundation for future research and practice on AI integration in teacher education.

6. Implications, Limitations and Suggestions

The findings of the study offer important implications for teacher education and the adoption of AI in educational contexts, particularly in English language teaching. The development and validation of this scale address a crucial research gap by providing a holistic instrument to measure pre-service teachers' acceptance, readiness, and intention to use AI in teaching English. As such, the scale may be useful for curriculum designers, teacher education institutions, and educational policymakers. The findings also highlight the importance of incorporating AI-focused modules into B.Ed. and M.Ed. programmes. Teacher training institutions may use the scale to target specific dimensions and design interventions that enhance trainees' confidence, competence, and preparedness to integrate AI tools into their future teaching practice. In parallel, potential barriers to successful AI integration may also be identified and addressed systematically.

However, the study has certain limitations. First, the focus on a single country limits the cultural and geographical generalizability of the findings. Second, the non-experimental cross-sectional design restricts the examination of temporal stability and changes in pre-service teachers' views of AI over time, while also limiting causal interpretation among the three constructs. Third, the exclusive use of quantitative self-report measures may introduce single-method bias, including social desirability bias and common method variance. Fourth, the scale is limited to English teaching contexts, which may reduce its applicability to pre-service teachers in other subject areas where AI integration may take different forms. Future research should undertake cross-validation of the scale across diverse educational contexts, subject domains, and countries. The participant base may also be extended to in-service teachers and teacher educators to strengthen the broader applicability of the instrument. In addition, qualitative studies may complement the present findings by offering deeper insights into teachers' experiences and perceptions. Longitudinal studies are also recommended to examine the stability of the three constructs over time.

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Author Contribution Statement

Sourav Choudhury: Conceptualization, Methodology, Writing- original draft preparation. Anamika Kar: Data Curation, Investigation, Writing - Reviewing & Editing. Priya Shukla and Rozina Khatun: Formal Analysis, Visualization, Supervision. All the authors have read and agreed to the published version of the manuscript. All the authors have read and agreed to the published version of the manuscript.

Does this article screen for similarity?

Yes

Conflict of Interest

The authors have no conflicts of interest to declare. There is also no financial interest to report. The author certifies that the submission is original work and is not under review at any other publication.

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