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ARTICLE

BEYOND TECHNOLOGY ACCEPTANCE: VALIDATING A MULTIDIMENSIONAL AI INTEGRATION READINESS SCALE FOR TEACHER EDUCATORS

Além da Aceitação Tecnológica: Validação de uma Escala Multidimensional de Prontidão para Integração da Inteligência Artificial na Formação de Professores

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ABSTRACT | Purpose: This study developed and validated the AI Teacher Education Tool (AITET), a psychometric instrument measuring teacher educators' readiness to incorporate artificial intelligence across various professional domains. **Methodology/Approach:** A quantitative cross-sectional design was used with 114 teacher educators from government, private, and government-aided institutions in Northern India. Instrument development was based on the Technology Acceptance Model (Davis, 1989) and Bandura's Self-Efficacy Theory (1997). Validation involved exploratory factor analysis (EFA), confirmatory factor analysis (CFA), reliability testing, and assessments of convergent and discriminant validity using Average Variance Extracted, the Fornell-Larcker criterion, and Heterotrait-Monotrait ratios. **Findings:** EFA identified a five-factor structure explaining 70.998% of total variance: Professional Integration and Administrative Utility, Teaching and Learning Applications, Research and Ethical Considerations, Learning Design and Content Creation, and Ethical Awareness and Policy Dimensions. The instrument demonstrated excellent reliability (overall $\alpha = 0.967$; subscale range: 0.864 to 0.919). Convergent validity was established across all five factors (AVE range: 0.555 to 0.701), and discriminant validity was confirmed through the HTMT criterion (all pairs below 0.85). CFA yielded an acceptable fit ($\chi^2/df = 1.97$; SRMR = 0.065), though incremental indices indicated room for improvement. **Research Limitations/Implications:** The study is geographically confined to Northern India, which restricts its generalisability. Although the sample is sufficient for EFA, it is relatively modest for CFA. The AITET has implications for professional development planning, institutional policy development, and AI literacy programme design. **Originality/Value:** The AITET expands technology acceptance frameworks to include domain-specific competencies, twin ethical constructs, and self-efficacy dimensions, filling a notable gap in psychometric measurement and offering a validated tool for assessing AI readiness in higher education.

Keywords | Artificial Intelligence, Teacher Education, Psychometric Validation, Technology Acceptance, Professional Development

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RESUMO | Objetivo: Este estudo desenvolveu e validou o *AI Teacher Education Tool* (AITET), um instrumento psicométrico destinado a mensurar a prontidão de formadores de professores para incorporar a inteligência artificial em diferentes domínios profissionais. **Metodologia:** Foi adotado um delineamento quantitativo transversal com 114 formadores de professores provenientes de instituições públicas, privadas e subvencionadas do norte da Índia. O desenvolvimento do instrumento baseou-se no Modelo de Aceitação de Tecnologia (Davis, 1989) e na Teoria da Autoeficácia de Bandura (1997). A validação incluiu análise fatorial exploratória (AFE), análise fatorial confirmatória (AFC), testes de confiabilidade e avaliações de validade convergente e discriminante por meio da Variância Média Extraída (AVE), critério de Fornell-Larcker e razão Heterotrait-Monotrait (HTMT). **Resultados:** A AFE identificou uma estrutura de cinco fatores explicando 70,998% da variância total: Integração Profissional e Utilidade Administrativa; Aplicações no Ensino e Aprendizagem; Pesquisa e Considerações Éticas; Design de Aprendizagem e Criação de Conteúdo; e Consciência Ética e Dimensões de Políticas. O instrumento demonstrou excelente confiabilidade (α geral = 0,967; intervalo das subescalas: 0,864 a 0,919). A validade convergente foi confirmada para todos os fatores (AVE entre 0,555 e 0,701), e a validade discriminante foi evidenciada pelo critério HTMT (todos os pares abaixo de 0,85). A AFC apresentou ajuste aceitável ($\chi^2/df = 1{,}97$; SRMR = 0,065), embora os índices incrementais indiquem espaço para aprimoramento. **Limitações/Implicações:** O estudo está geograficamente restrito ao norte da Índia, o que limita sua generalização. Embora a amostra seja adequada para AFE, é relativamente reduzida para AFC. O AITET possui implicações relevantes para o planejamento de desenvolvimento profissional, formulação de políticas institucionais e desenho de programas de letramento em IA. **Originalidade/Valor:** O AITET amplia os modelos de aceitação tecnológica ao incorporar competências específicas de domínio, constructos éticos duais e dimensões de autoeficácia, preenchendo uma lacuna relevante na mensuração psicométrica e oferecendo uma ferramenta validada para avaliar a prontidão para IA no ensino superior.

Palavras-chave | Inteligência Artificial; Formação de Professores; Validação Psicométrica; Aceitação de Tecnologia; Desenvolvimento Profissional

INTRODUCTION

The emergence of artificial intelligence (AI) as a transformative force in education presents complex challenges for teacher educators, who play a pivotal role in preparing future-ready professionals. As key agents in this transition, they are expected to both adapt personally and foster AI competence among pre-service teachers (Salas-Pilco et al., 2022; Yang et al., 2025). The successful integration of AI into teacher education depends on educators' perceptions, self-efficacy, and attitudes toward these rapidly evolving technologies.

Systematic reviews highlight a limited understanding of teacher educators' preparedness for AI adoption. Celik et al. (2022) report multiple barriers, including inadequate professional development, concerns over academic integrity, and insufficient awareness of AI capabilities. Despite the widespread availability of AI tools, their uptake remains low; Kaufman et al. (2025) found that only 25% of U.S. teachers used AI in instructional planning during the 2023–2024 academic year.

AI integration involves more than adopting tools; it requires competencies across curriculum design, research, administration, and ethical judgment (Ng et al., 2023; Chiu, 2024). Existing instruments primarily address general technology acceptance, lacking the scope to evaluate domain-specific readiness for AI. Newer tools, such as the Readiness for Artificial Intelligence Applications Scale (RAIS), signal a shift toward multidimensional assessment (Ramazanoglu & Akın, 2024).

Addressing this gap, the present study develops and validates the AI Teacher Education Tool (AITET), a comprehensive instrument that measures readiness for AI integration across professional domains. It also addresses growing concerns about ethics, trust, and academic integrity associated with generative AI technologies (Walter, 2024; Yang et al., 2025).

LITERATURE REVIEW

Theoretical Foundations of Technology Acceptance

The Technology Acceptance Model (TAM), originally proposed by Davis (1989), remains one of the most widely used frameworks for understanding how individuals adopt new technologies in educational settings. Essentially, TAM suggests that perceived usefulness and perceived ease of use are the main factors influencing the behavioural intention to use a technology. The strength of these constructs has been extensively validated within educational contexts. Meta-analytic evidence from Scherer et al. (2019), synthesising 114 studies involving over 36,000 teachers, confirmed perceived usefulness as the strongest predictor of behavioural intentions ($\beta = .52$), followed by perceived ease of use ($\beta = .33$). Granić and Marangunić (2019) further supported the explanatory power of TAM's core variables through a systematic literature review, while also identifying a crucial limitation: the model's original constructs were developed for general technology adoption and need to be adapted for specific domains, especially when applied to emerging technologies like artificial intelligence. This limitation is particularly significant in teacher education contexts, where technology adoption involves not only technical skills but also complex professional judgments involving pedagogy, ethics, and institutional responsibility.

Bandura's Self-Efficacy Theory (1997) offers a crucial complementary foundation for understanding why technology acceptance alone is insufficient to explain AI integration behaviour among educators. Self-efficacy, an individual's belief in their ability to perform a specific action, directly influences both the decision to adopt a technology and the quality of its implementation (Pfitzner-Eden, 2016). In the context of AI, educators with strong self-efficacy beliefs are more likely to experiment with AI tools, persevere through initial challenges, and implement AI intentionally in their professional practice. The integration of self-efficacy theory with TAM thus advances understanding beyond attitudinal acceptance towards a more complete account of readiness for practice.

Recent scholarship has expanded these fundamental frameworks to address the specific challenges that artificial intelligence presents to teachers' professional knowledge. Celik (2023) introduced the Intelligent-TPACK framework, which enhances the existing Technological, Pedagogical, and Content Knowledge (TPACK) model by adding a clear ethical component, arguing that effective AI integration requires teachers to critically evaluate AI-based decisions, not just to operate AI tools competently. Findings from this study showed that technological knowledge alone is not enough for educational AI integration; instead, it must be combined with pedagogical knowledge and ethical awareness to achieve meaningful instructional results. This has direct implications for instrument design, as it indicates that any comprehensive measure of AI readiness needs to include ethical and pedagogical aspects alongside technical skills. Chiu (2024) also extended existing frameworks by developing the Teacher Artificial Intelligence Competence Self-Efficacy (TAICS) scale, which covers six areas: AI knowledge, pedagogy, assessment, ethics, human-centred education, and professional engagement, providing further empirical evidence that AI readiness in teacher education is inherently multidimensional.

Taken together, these theoretical developments point to a clear and consistent conclusion: TAM, while foundational, requires substantial extension to adequately capture AI integration readiness in professional educational contexts. The present study responds to this challenge by grounding the AITET in both TAM and self-efficacy theory, and by incorporating AI-specific dimensions of ethics, trust, and domain-specific competence that existing technology acceptance frameworks do not fully address. This multi-theoretical approach positions the AITET to encompass both the attitudinal dimensions identified by Davis (1989) and the competency and ethical considerations highlighted in more recent scholarship (Celik, 2023; Chiu, 2024).

AI Integration in Teacher Education: Current State and Challenges

Despite the widespread availability of AI tools, evidence consistently highlights a considerable gap between AI's potential in teacher education and its real-world application, exposing deficiencies in professional training, institutional support, and readiness evaluation.

Systematic reviews show that this gap remains persistent and multi-faceted. Celik et al. (2022) identified barriers faced by teacher educators, including a lack of professional development, concerns about academic integrity, and limited understanding of AI capabilities. Salas-Pilco et al. (2022) reviewed 30 studies from 16 countries and found that AI adoption in education trails behind other sectors, with concerns about pedagogical displacement growing alongside the increase of generative AI tools (Ng et al., 2023).

Quantitative evidence supports this view. Kaufman et al. (2025) found that only 25% of teachers in the United States used AI for lesson planning during 2023 to 2024, with schools in higher-poverty areas showing lower adoption rates. These patterns confirm that readiness is unevenly distributed and that institutional and demographic factors influence adoption in ways that generic technology acceptance frameworks do not account for.

At the policy level, Miao and Cukurova (2024) note that as of 2022, only seven countries had developed national AI competency frameworks for teachers. Their UNESCO AI Competency Framework defines 15 competencies across five dimensions, including AI pedagogy, ethics, and professional development, highlighting the urgency and complexity of the measurement challenge.

Collectively, this evidence demonstrates the need for a theoretically grounded, psychometrically robust instrument capable of diagnosing AI readiness across the professional domains that teacher educators operate in, which is the specific gap the AITET was developed to fill.

Ethical Considerations and Trust in AI Educational Applications

The integration of AI into teacher education presents a unique set of ethical challenges that go well beyond the issues covered by traditional technology acceptance models. These challenges, including algorithmic bias, data privacy, academic integrity, and educational inequality, have become key concerns in recent research and must be considered in any thorough assessment of AI preparedness (Holmes et al., 2022).

Academic integrity has become increasingly important with the recent capabilities of contemporary AI systems. Foltynek et al. (2023) argue that AI's ability to generate content that appears original fundamentally challenges established norms of authorship and scholarly attribution, necessitating that educators develop both policy awareness and practical approaches to uphold integrity in AI-supported learning environments. This issue is not incidental; it directly influences how teacher educators view, trust, and interact with AI tools in their professional roles.

Trust has become a key construct that functions alongside and beyond traditional TAM variables. Choi et al. (2023) demonstrated that pedagogical beliefs and perceived trust independently influence teachers' acceptance of AI tools, with transparency, reliability, and institutional alignment identified as important trust factors. These findings indicate that measuring AI readiness without considering trust-related aspects provides an incomplete picture.

Walter (2024) further contends that AI literacy must include critical thinking and ethical awareness as fundamental skills, not optional extras. This view aligns with the AITET's design philosophy, which considers ethical awareness and research integrity as separate, measurable aspects of teacher educator preparedness rather than assumed prerequisite conditions.

Professional Development and AI Literacy

Effective AI integration in teacher education depends on systematic professional development that covers technical skills, pedagogical use, and ethical concerns in a cohesive way. Despite this recognised need, AI literacy remains underdeveloped in most teacher education programmes, with preparation efforts often fragmented, inconsistent, and not well grounded in validated frameworks (Ng et al., 2021; Yang et al., 2025).

Recent research has advanced both the conceptualisation and measurement of AI literacy. Allen and Kendeou (2024) proposed the ED-AI Lit framework, a multidisciplinary model comprising six components: Knowledge, Evaluation, Collaboration, Contextualisation, Autonomy, and Ethics. This framework argues that AI literacy must extend beyond technical proficiency to include critical evaluation of AI outputs, ethical reasoning, and the ability to contextualise AI use within relevant educational and societal settings. Yang et al. (2025), through a bibliometric analysis of AI literacy research from 2014 to 2024, identified nine emerging research themes, demonstrating a progression from exploratory investigations to systematic integration efforts and indicating a growing consensus on the multifaceted nature of AI literacy.

At the instrument level, Chiu (2024) validated the TAICS scale across six dimensions of AI competence, and Ramazanoglu and Akin (2024) developed the RAIS, addressing technology self-efficacy, student interaction, and ethical awareness. Celik (2023) further demonstrated that professional knowledge for AI integration must incorporate ethical assessment alongside technological and pedagogical knowledge.

These developments collectively affirm that professional development for AI readiness demands structured, evidence-based approaches and that valid measurement tools are essential for designing and evaluating such programmes effectively.

Measurement Challenges and Research Gaps

Despite advances in AI literacy research, notable measurement gaps remain. Existing tools mainly focus on student perspectives or general technology acceptance, failing to capture the unique professional responsibilities of teacher educators across various domains (Granić & Marangunić, 2019). Most available instruments evaluate either attitudinal aspects or narrow technical skills, without integrating the pedagogical, administrative, research, and ethical aspects that define the full scope of a teacher educator's professional role.

Three essential gaps justify the development of the AITET. First, existing instruments lack a domain-specific focus for teacher educators, whose professional responsibilities include teaching, learning design, scholarly research, institutional administration, and ethical governance — a breadth that single-construct or general technology acceptance measures cannot adequately capture. Second, available tools fail to incorporate established theoretical frameworks with AI-specific concerns such as trust, academic integrity, and ethical policy awareness, resulting in instruments that are theoretically incomplete for today's educational landscape. Third, the lack of fully validated instruments limits evidence-based professional development and institutional policy development.

Recent developments show promise. Chai et al. (2024) developed the AILIS, incorporating the Theory of Planned Behaviour and the Technology Readiness Index. Chiu (2024) and Ramazanoglu and Akin (2024) have similarly advanced multidimensional approaches to measuring AI readiness. However, none of these instruments addresses the specific professional context of teacher educators in higher education with the theoretical depth and psychometric rigour that the present study proposes.

The AITET was designed to directly tackle these limitations, offering a validated, theoretically based, and domain-specific measure of AI integration readiness in teacher education.

The foregoing review identifies a coherent and cumulative case for the present study. Technology acceptance frameworks provide a robust theoretical starting point but require substantive extension to address the domain-specific competencies, ethical dimensions, and trust-related factors that characterise AI integration in teacher education. Existing instruments are theoretically incomplete and fail to meet the diagnostic needs of institutions seeking to systematically support educator readiness. The AITET was developed to fill this gap by operationalising AI integration readiness across the professional domains most relevant to teacher educators, grounded in validated theory and subjected to rigorous psychometric scrutiny. The research objectives that follow reflect this integrated theoretical and empirical agenda.

RESEARCH OBJECTIVES

The study has the following research objectives:

1) To establish the factorial structure of the AI Teacher Education Tool through Exploratory Factor Analysis and identify underlying constructs of teacher educators' AI integration readiness.
2) To validate the factorial structure through Confirmatory Factor Analysis and assess model fit using established goodness-of-fit indices.
3) To evaluate the internal consistency reliability of all AITET subscales and establish measurement precision.
4) To establish convergent and discriminant validity evidence through multiple psychometric criteria.
5) To provide comprehensive implementation guidelines, scoring procedures, and normative data for research and institutional applications.

RESEARCH METHODOLOGY

Research Design

This study utilised a quantitative cross-sectional design following established psychometric validation protocols. The primary aim was to develop and validate the AI Teacher Education Tool (AITET), which assesses teacher educators' perceptions, self-efficacy, and attitudes towards AI integration across various professional roles.

The validation employed a five-phase structure that aligns with best practices in educational measurement (Boateng et al., 2018; DeVellis, 2017; Worthington & Whittaker, 2006): (1) exploratory factor analysis (EFA); (2) confirmatory factor analysis (CFA); (3) reliability testing; (4) convergent and discriminant validity evaluation; and (5) implementation framework development. This design addresses the call for greater methodological rigour in AI education research.

Theoretical Framework

AITET's development was anchored in the Technology Acceptance Model (Davis, 1989) and Bandura's Self-Efficacy Theory (1997). TAM informed the constructs of perceived usefulness and ease of use, while the self-efficacy theory addressed confidence in AI implementation. The tool also integrated insights from recent AI-specific research, incorporating dimensions of trust, ethics, and institutional support (Chiu, 2024).

Participants and Sampling

A total of 114 teacher educators from Northern India took part. The sample consisted of 34 males (29.8%) and 80 females (70.2%), representing government (18.4%), private (43.9%), and government-aided (37.7%) institutions. The majority of participants had over 10 years of teaching experience (71%), and 65.8% possessed doctoral qualifications. Academic positions included Assistant Professors (57.9%), Associate Professors (17.5%), Professors (10.5%), and others (14.0%).

Although 65.8% lacked formal AI training, 44.7% reported using AI tools weekly or more frequently, with 34.2% using them daily.

A two-stage sampling procedure was implemented. In the first stage, institutions were purposively selected based on documented evidence of faculty engagement with AI tools, including institutional AI policies, technology integration initiatives, and reported AI usage among teaching staff. This criterion-based selection ensured that participants possessed sufficient familiarity with AI to provide meaningful responses. In the second stage, a random sampling approach was applied within each selected institution, in which all eligible teacher educators were assigned unique identifiers, and participants were selected using a random-number procedure. This combination of purposive institutional selection and within-institution random sampling sought to balance the need for AI-relevant respondents with the representativeness requirements of psychometric validation research. To address potential sampling bias, the demographic profile of the final sample was examined against publicly available institutional staffing records where accessible, confirming broad alignment across gender, designation, and institutional type.

It is acknowledged that a sample of 114 participants, though meeting minimum thresholds for exploratory factor analysis, is on the lower boundary for confirmatory factor analysis procedures. Kline (2016) recommends a minimum of 200 participants for stable CFA parameter estimation, and the present sample falls below this benchmark. However, several mitigating factors support the adequacy of the current sample for this initial validation study. Model complexity was moderate, with factor loadings concentrated and above acceptable thresholds, and convergence was achieved without anomalous results. Hair et al. (2019) note that smaller sample sizes may be acceptable when communalities are high, and the factor solution is well-defined, both conditions satisfied in the present study. Future validation studies with larger and more geographically diverse samples are recommended to confirm the stability of the factor structure.

Instrument Development

The item construction process was guided by a theory-driven approach, drawing on literature related to technology acceptance and AI integration in education. The AITET comprised 46 items across three scales:

- **AI Perceptions Scale (30 items):** Comprising six subdomains, each containing five items: Teaching and Learning, Learning Design, Research and Academic Writing, Administrative Work, Professional Development, and Ethical/Policy Awareness.
- **Self-Efficacy Scale (8 items)**: Assessing confidence in AI utilisation.
- **Attitudes Scale (8 items)**: Assessing dispositions and behavioural intentions.

A five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) was used. The tool also captured demographic data, such as gender, qualification, designation, experience, training background, and AI usage patterns.

Data Collection Procedure

Data were collected online via Google Forms in May 2025. Randomised invitations were distributed to teacher educators in purposively selected institutions. Sufficient time was provided to encourage participation while ensuring consistency in data capture.

Ethical Considerations

Institutional ethical clearance was obtained beforehand. Participants provided informed consent and were assured of confidentiality and voluntary participation. No identifiable information was collected, and all data was securely stored with restricted access.

DATA ANALYSIS STRATEGY

A five-phase analytical approach was adopted using SPSS v26.0 and AMOS v24.0:

1. **Preliminary Analysis**: Checked for missing data, outliers (z-scores), and normality. Sampling adequacy was tested using KMO and Bartlett's test.
2. **Exploratory Factor Analysis (EFA)**: Conducted using Principal Component Analysis with Varimax rotation. Factor retention was based on eigenvalues > 1.0, scree plots, loadings ≥ .50, minimal cross-loadings (< .30), and communalities ≥ .40.
3. **Confirmatory Factor Analysis (CFA)**: Assessed model fit using χ^2/df (< 3.0), *CFI* (≥ .90), *TLI* (≥ .90), *RMSEA* (≤ .08), and *SRMR* (≤ .08).
4. **Reliability Testing**: Evaluated using Cronbach's alpha and Composite Reliability; thresholds ≥ .70 were considered acceptable.
5. **Validity Assessment**: Convergent validity assessed via *AVE* (≥ .50) and loadings (≥ .50). Discriminant validity was evaluated using Fornell-Larcker criteria and HTMT ratios (< .85 conservative).

Minimal missing data (<2%) were handled via listwise deletion due to random distribution. Significance was determined at $\alpha < 0.05$.

METHODOLOGICAL LIMITATIONS

The study is geographically limited to Northern India, which may affect its generalisability. The cross-sectional design restricts temporal inferences. While theory-driven and psychometrically rigorous, formal expert panel validation was not conducted during this phase. These limitations inform future work involving longitudinal and cross-cultural validation.

RESULTS OF THE STUDY

The results of this psychometric validation study are presented in accordance with the five research objectives, providing a comprehensive analysis of the AI Teacher Education Tool's (AITET) factorial structure, reliability, and validity. Statistical analyses were conducted using SPSS version 26.0, with significance levels set at $\alpha = .05$ for all tests. The dataset comprised complete responses from all 114 participants, with no missing values across any variables, indicating robust data collection procedures and high participant engagement. The results demonstrate the development of a psychometrically sound instrument with strong potential for measuring teacher educators' readiness for integrating AI across multiple professional domains.

Objective 1: Factorial Structure Development through Exploratory Factor Analysis

Preliminary Analysis and Data Suitability

Prior to conducting the exploratory factor analysis, the suitability of the data for factor extraction was evaluated through established statistical criteria. The preliminary analysis confirmed that the dataset met all requirements for robust factor analysis.

As shown in Table 1, the Kaiser-Meyer-Olkin (KMO) measure yielded an excellent value of .914, indicating sampling adequacy well above the minimum threshold of 0.60. Bartlett's Test of Sphericity was significant ($\chi^2 = 2830.731$, $df = 435$, $p < 0.001$), confirming that correlations were appropriate for factor extraction.

Table 1. KMO and Bartlett's Test Results

Test	Statistic	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	KMO	.914
Bartlett's Test of Sphericity	Approx. Chi-Square	2830.731
	df	435
	Significance	p < 0.001

Factor Extraction and Retention

EFA revealed a five-factor solution based on eigenvalues >1.0 and scree plot inspection. These five components cumulatively explained 70.998% of total variance, with the rotated variance contributions detailed in Table 2.

Table 2. Total Variance Explained by Extracted Components

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	15.554	51.846	51.846	4.962	16.541	16.541
2	1.828	6.093	57.939	4.476	14.919	31.460
3	1.566	5.221	63.160	4.317	14.391	45.852
4	1.279	4.262	67.422	4.228	14.093	59.944
5	1.073	3.576	70.998	3.316	11.053	70.998

A distinct elbow in the scree plot (Figure 1) supported the five-factor extraction, suggesting a stable and interpretable structure.

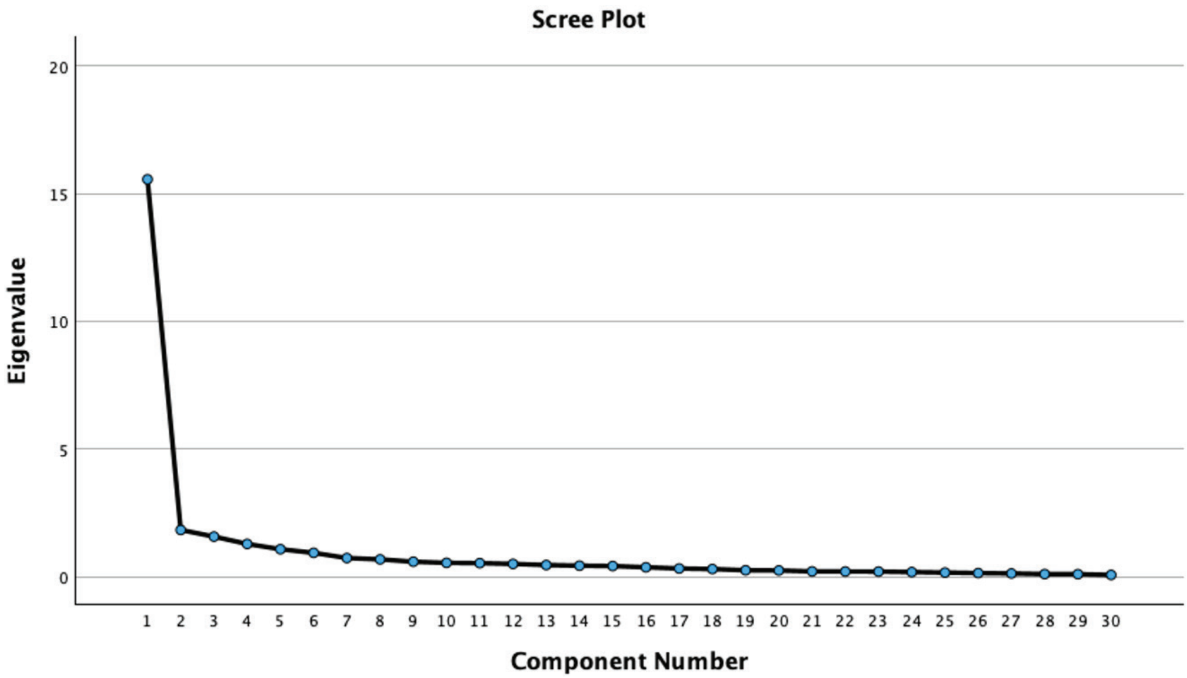

Figure 1. Scree Plot of Eigenvalues for AI Perceptions Scale (30 items)

Communalities and Item Retention

Communality values ranged from 0.555 to 0.813, with most items exceeding 0.65, indicating strong representation by the extracted components. Only item PD3 had a slightly lower communality (0.555) but met the inclusion threshold (≥ 0.40).

Rotated Component Matrix

The rotated structure (Table 3) showed items with primary loadings ≥ 0.50 and minimal cross-loadings (< 0.30). Based on the item content, the five factors were interpreted as follows:

Table 3. Rotated Component Matrix - Factor Loadings ≥ 0.50

Item	Component 1	Component 2	Component 3	Component 4	Component 5
Component 1: Professional Integration and Administrative Utility					
AW1	**.719**	.359	.155	.185	.162
AW2	**.678**	.126	.207	.426	.164
AW3	**.753**	.173	.241	.287	.039
AW4	**.689**	.075	.506	.130	.244
AW5	**.725**	.201	.232	.194	.097
PD2	**.521**	.524	.167	.262	.085
PD4	**.548**	.265	.608	.118	.154
Component 2: Teaching and Learning Applications					
TL2	.351	**.560**	-.128	.353	.249
TL3	.035	**.728**	.324	.152	.230
TL4	.144	**.693**	.311	.280	.212
TL5	.272	**.762**	.241	.157	.070
PD5	.329	**.489**	.585	-.027	.158
Component 3: Research and Ethical Considerations					
RA2	.220	.192	**.730**	.338	.114
RA3	.192	.184	**.695**	.397	.243
RA4	.287	.161	**.733**	.204	.265
RA5	.286	.237	**.584**	.406	.230
Component 4: Learning Design and Content Creation					
LD2	.334	.244	.318	**.586**	.201
LD3	.342	.263	.260	**.603**	.236
LD4	.284	.388	.227	**.653**	.194
LD5	.290	.286	.279	**.726**	.162
RA1	.215	.292	.502	**.535**	.110
PD1	.251	.365	.275	**.547**	.284
Component 5: Ethical Awareness and Policy Dimensions					
EP1	-.012	.193	.216	.243	**.758**
EP2	.164	.175	.089	-.060	**.808**
EP3	.144	.101	.178	.252	**.764**
EP4	.243	.180	.264	.441	**.618**

Note: Factor loadings ≥ .50 are shown in bold. Items with primary loadings < .50 or excessive cross-loadings were excluded from the final factor structure.

Factor Interpretation and Naming

Based on the content analysis of items with substantial loadings (≥ 050) shown in Table 3, the five extracted components were conceptually interpreted and labelled as follows:

- **Component 1: Professional Integration and Administrative Utility (16.54%)**
  Includes items AW1–AW5, PD2, and PD4, capturing AI's perceived utility in administrative, institutional, and professional development activities.
- **Component 2: Teaching and Learning Applications (14.92%)**
  Comprises TL2–TL5 and PD5, reflecting AI's role in instructional design, student interaction, and pedagogical practices.
- **Component 3: Research and Ethical Considerations (14.39%)**
  Includes RA2–RA5, representing AI's application in academic writing and ethical issues within scholarly contexts.
- **Component 4: Learning Design and Content Creation (14.09%)**
  Encompasses LD2–LD5, RA1, and PD1, focusing on AI's role in content development and instructional design.
- **Component 5: Ethical Awareness and Policy Dimensions (11.05%)**
  Consists of EP1–EP4, capturing concerns around policy, academic integrity, and ethical use of AI.

Excluded Items

Three items, TL1, LD1, and EP5, were excluded due to low loadings (< 0.50) or excessive cross-loading, resulting in a final 24-item perception scale.

Factor Structure Validation

The five-factor model demonstrated conceptual clarity and statistical robustness. All retained items had strong loadings, the total explained variance exceeded the 60% benchmark for social sciences, and factor sizes were balanced (4–7 items each). The structure reflects distinct yet complementary dimensions of teacher educators' perceptions of AI, offering empirical support for the instrument's multidimensional design.

These findings provide a sound empirical foundation for the confirmatory analysis reported under Objective 2.

Objective 2: Structural Validation through Confirmatory Factor Analysis

To validate the five-factor structure identified through exploratory factor analysis, confirmatory factor analysis was conducted using maximum likelihood estimation (N = 114). The CFA tested the hypothesised model with five latent constructs: Professional Integration and Administrative Utility (7 items), Teaching and Learning Applications (5 items), Research and Ethical Considerations (4 items), Learning Design and Content Creation (6 items), and Ethical Awareness and Policy Dimensions (4 items).

Model Fit Assessment

Table 4. Confirmatory Factor Analysis Fit Indices

Fit Index	Obtained Value	Threshold	Interpretation
χ^2/df	1.97	< 3.0	Good fit
CFI	.876	≥ .90	Approaching acceptable
TLI	.861	≥ .90	Approaching acceptable
RMSEA	.092	≤ .08	Marginal fit
SRMR	.065	≤ .08	Good fit

Model fit indices are presented in Table 4. The χ^2/df ratio of 1.97 suggests a good fit, while the *SRMR* (.065) also met the accepted standard (≤ .08). However, *CFI* (.876) and *TLI* (.861) approached but did not reach the .90 threshold. *RMSEA* (.092, 90% CI [.081–.103] indicated marginal fit.

Factor Loadings and Construct Validity

Table 5. Standardised Factor Loadings and Significance Tests

Factor	Item	Standardised Loading	SE	*z-value*	*p-value*
Professional Integration	AW1	.791	.077	9.96	< 0.001
	AW2	.800	.075	10.12	< 0.001
	AW3	.806	.075	10.23	< 0.001
	AW4	.835	.071	10.81	< 0.001
	AW5	.749	.083	9.19	< 0.001
	PD2	.718	.079	8.67	< 0.001
	PD4	.801	.071	10.14	< 0.001
Teaching & Learning	TL2	.619	.092	7.03	< 0.001
	TL3	.773	.086	9.46	< 0.001
	TL4	.847	.077	10.83	< 0.001
	TL5	.777	.085	9.52	< 0.001
	PD5	.687	.083	8.02	< 0.001
Research & Ethics	RA2	.812	.085	10.30	< 0.001
	RA3	.867	.075	11.43	< 0.001
	RA4	.837	.079	10.79	< 0.001
	RA5	.832	.081	10.71	< 0.001

Factor	Item	Standardised Loading	SE	*z-value*	*p-value*
Learning Design	LD2	.792	.075	9.99	< 0.001
	LD3	.815	.075	10.43	< 0.001
	LD4	.842	.074	10.99	< 0.001
	LD5	.854	.071	11.24	< 0.001
	RA1	.757	.080	9.35	< 0.001
	PD1	.776	.081	9.71	< 0.001
Ethical Awareness	EP1	.705	.088	8.24	< 0.001
	EP2	.594	.093	6.62	< 0.001
	EP3	.820	.074	10.19	< 0.001
	EP4	.871	.076	11.12	< 0.001

All standardised loadings (Table 5) were statistically significant ($p < 0.001$), ranging from .594 to .871, with most exceeding the preferred threshold of .70. The most substantial loadings were observed for the Research and Ethics factor (.812–.867), whereas EP2 had the lowest loading (.594) but remained acceptable. Inter-Factor Correlations

Table 6. Inter-Factor Correlations

Factor	1	2	3	4	5
1. Professional Integration	1.000				
2. Teaching & Learning	.740	1.000			
3. Research & Ethics	.795	.732	1.000		
4. Learning Design	.817	.807	.832	1.000	
5. Ethical Awareness	.607	.639	.692	.717	1.000

Inter-factor correlations ranged from .607 to .832 (Table 6), all below the conservative .85 threshold, confirming discriminant validity. The strongest correlation was between Learning Design and Research & Ethics ($r = .832$); the weakest was between Professional Integration and Ethical Awareness ($r = .607$).

Model Validation Summary

The CFA supports the theoretical five-factor structure identified in the EFA. Despite CFI and TLI values falling slightly short of conventional benchmarks, the model demonstrated several indicators of construct validity. All factor loadings were statistically significant and above the minimum threshold of .50, with the majority exceeding the preferred criterion of .70. Absolute fit indices were acceptable, with $\chi^2/df = 1.97$ and SRMR = .065 both meeting recommended standards. Inter-factor correlations remained below .85 across all factor pairs, confirming adequate discriminant validity. Taken together, these findings affirm that the AITET possesses sound construct validity, supporting its use as a multidimensional instrument for assessing AI integration readiness among

Review of Artificial Intelligence in Education. Florida (EUA), v. 7, e082, 2026.

teacher educators. The marginal performance on incremental fit indices is addressed further in the Discussion section.

Objective 3: Reliability Assessment

To evaluate the internal consistency of the AI Teacher Education Tool (AITET), Cronbach's alpha and composite reliability (CR) scores were calculated for all subscales based on the complete dataset (N = 114), which contained no missing values.

As shown in Table 7, all Cronbach's alpha coefficients exceeded .864, indicating strong internal consistency. The overall AI Perceptions Scale (30 items) had the highest alpha (α = .967), indicating excellent internal consistency. Subdomains such as *Learning Design* (α = .912) and *Research and Academic Writing* (α = .911) also exhibited excellent reliability.

Table 7. Internal Consistency Reliability for AI Teacher Education Tool Scales

Scale/Subscale	Number of Items	Cronbach's α	Composite Reliability	Reliability Level
Overall Perceptions Scale	30	.967	-	Excellent
Original Perception Domains				
AI in Teaching and Learning	5	.872	.860	Good
AI in Learning Design and Content Creation	5	.912	.918	Excellent
AI in Research and Academic Writing	5	.911	.904	Excellent
AI in Administrative and Institutional Work	5	.900	.919	Excellent
AI in Professional Development and Collaboration	5	.867	-	Good
Awareness of Ethical and Policy Dimensions	5	.864	.839	Good
CFA-Derived Factors				
Professional Integration and Administrative Utility	7	-	.919	Excellent
Teaching and Learning Applications	5	-	.860	Good
Research and Ethical Considerations	4	-	.904	Excellent
Learning Design and Content Creation	6	-	.918	Excellent
Ethical Awareness and Policy Dimensions	4	-	.839	Good
Additional Scales				
Self-Efficacy Scale	8	.945	-	Excellent
Attitudes Towards AI	8	.922	-	Excellent

Note: Reliability levels based on conventional thresholds: ≥ 0.90 = Excellent, .80-.89 = Good, .70-.79 = Acceptable (Nunnally & Bernstein, 1994)

Composite reliability values for CFA-derived factors ranged from .839 to .919, exceeding the recommended minimum of .70 (Fornell & Larcker, 1981). The highest CR was recorded for Professional Integration (.919), whereas the lowest, Ethical Awareness (.839), still fulfilled acceptable standards. CR is preferred in SEM contexts as it incorporates item loadings (Raykov, 1997).

Self-Efficacy and Attitudes Scales

Both additional scales exhibited excellent internal consistency. The Self-Efficacy Scale ($\alpha = .945$) aligns with established standards in educational technology research (Tschannen-Moran & Hoy, 2001). The Attitudes Towards AI scale ($\alpha = .922$) meets benchmarks for attitudinal measures in technology acceptance research (Venkatesh et al., 2003).

Item-Total Correlations

Item-total correlations ranged from .435 to .862, with the majority of items exceeding .70, indicating strong item discrimination and contribution to overall scale coherence (Field, 2018; Pallant, 2020). The lowest acceptable value (.435) was for EP2 in the Ethical Awareness scale, which remains within acceptable thresholds (Nunnally & Bernstein, 1994).

Summary

These results affirm the AITET's strong reliability and internal consistency, in line with psychometric standards for educational instruments (American Educational Research Association et al., 2014). The consistently high coefficients across all subscales and domains validate its utility for robust, multidimensional assessment in educational research and practice.

Objective 4: Validity Evaluation

Construct validity of the AI Teacher Education Tool (AITET) was assessed through convergent and discriminant validity following established psychometric guidelines (Fornell & Larcker, 1981; Hair et al., 2019). Convergent validity was evaluated using Average Variance Extracted (AVE), Composite Reliability (CR), and factor loadings. In contrast, discriminant validity was examined via the Fornell–Larcker criterion and Heterotrait–Monotrait (HTMT) ratio (Henseler et al., 2015).

Convergent Validity Assessment

As shown in Table 8, all five constructs exhibited strong convergent validity. Composite Reliability values ranged from .839 to .919, surpassing the recommended threshold of .70 (Fornell & Larcker, 1981). AVE values varied from .555 to .701, indicating that each construct accounted for more than 50% of the variance in its items (Hair et al., 2019).

Table 8. Convergent Validity Assessment

Factor	Items	Composite Reliability	Average Variance Extracted	Factor Loading Range	Convergent Validity
Professional Integration	7	.919	.619	.718 - .835	Excellent
Teaching & Learning	5	.860	.555	.619 - .847	Excellent
Research & Ethics	4	.904	.701	.812 - .867	Excellent
Learning Design	6	.918	.651	.757 - .854	Excellent
Ethical Awareness	4	.839	.570	.594 - .871	Good

Note: Convergent validity criteria: CR ≥ .70, AVE ≥ .50, Factor loadings ≥ .50

All standardised factor loadings exceeded .594, with the majority surpassing .70, thereby meeting the recommended criteria for convergent validity (Anderson & Gerbing, 1988). The Research & Ethics factor demonstrated the strongest convergence (loadings: 0.812–0.867), whereas Ethical Awareness exhibited acceptable but more variable performance (0.594–0.871).

Discriminant Validity Assessment: Fornell-Larcker Criterion

As per Table 9, two factors, *Research & Ethics* and *Ethical Awareness*, met the Fornell–Larcker criterion, where the square root of AVE exceeds the highest inter-factor correlation. Three other factors showed marginally lower √AVE than their maximum inter-construct correlation, suggesting strong conceptual alignment but not redundancy (Fornell & Larcker, 1981; Henseler et al., 2015).

Table 9. Fornell-Larcker Criterion Assessment

Factor	√AVE	Highest Inter-Factor Correlation	Discriminant Validity
Professional Integration	.787	.817	Marginal
Teaching & Learning	.745	.807	Marginal
Research & Ethics	.837	.832	✓ Achieved
Learning Design	.807	.832	Marginal
Ethical Awareness	.755	.717	✓ Achieved

Discriminant Validity Assessment: Heterotrait-Monotrait (HTMT) Ratio

The HTMT criterion provided stronger evidence for discriminant validity. All ten factor pairs reported HTMT values below the conservative threshold of .85 (Henseler et al., 2015), supporting the empirical distinction among constructs, as shown in Table 10.

Table 10. Inter-Factor Correlations and HTMT Assessment

Factor Pair	Correlation	HTMT Status	Discriminant Validity
Professional Integration - Teaching & Learning	.740	Pass (< 0.85)	✓ Achieved
Professional Integration - Research & Ethics	.795	Pass (< 0.85)	✓ Achieved
Professional Integration - Learning Design	.817	Pass (< 0.85)	✓ Achieved
Professional Integration - Ethical Awareness	.607	Pass (< 0.85)	✓ Achieved
Teaching & Learning - Research & Ethics	.732	Pass (< 0.85)	✓ Achieved
Teaching & Learning - Learning Design	.807	Pass (< 0.85)	✓ Achieved
Teaching & Learning - Ethical Awareness	.639	Pass (< 0.85)	✓ Achieved
Research & Ethics - Learning Design	.832	Pass (< 0.85)	✓ Achieved
Research & Ethics - Ethical Awareness	.692	Pass (< 0.85)	✓ Achieved
Learning Design - Ethical Awareness	.717	Pass (< 0.85)	✓ Achieved

Theoretical Coherence and Validity Summary

Convergent validity was fully satisfied across all five constructs, with average CR (.888) and AVE (.619) substantially exceeding the criteria proposed by Bagozzi and Yi (1988). Although the Fornell-Larcker results were mixed, with two of five factors fully meeting the criterion, the HTMT ratios confirmed discriminant validity across all factor pairs, providing stronger overall evidence of construct distinctiveness (Henseler et al., 2015). The Research and Ethics construct exhibited the strongest validity profile, with the highest AVE and consistently high factor loadings. The observed correlation structure reflects nomological validity (Cronbach & Meehl, 1955), with stronger relationships emerging between conceptually proximate constructs and weaker relationships between more theoretically distinct dimensions, consistent with the theoretical underpinnings of the Technology Acceptance Model and Self-Efficacy Theory (Kline, 2016). These validity findings are discussed further in relation to the instrument's theoretical contributions in the Discussion section.

Objective 5: Implementation Framework Development

To enhance the utility of the AI Teacher Education Tool (AITET) across educational settings, a structured implementation framework was developed. This framework includes instrument specifications, administration protocols, scoring procedures, interpretive benchmarks, and research applications. It ensures methodological rigour while accommodating contextual diversity in AI integration research.

The implementation framework presented in this section is grounded directly in the psychometric evidence established through the preceding validation phases. The factor structure, reliability coefficients, validity indicators, and normative data reported above collectively inform the specifications, scoring procedures, and interpretive guidelines detailed below. Rather than constituting a standalone prescriptive framework, this section translates the empirical findings into practical tools for researchers and institutions, ensuring that the AITET's application remains consistent with its validated measurement properties.

Validated Instrument Structure and Specifications

The final AITET includes **26 items** across seven validated constructs (see Table 11). The AI Perceptions section contains 24 items across five factors; the Self-Efficacy and Attitudes subscales each retain eight items. All items use a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Reliability coefficients (α = 0.864–0.967) and Composite Reliability (CR = 0.839–0.919) confirm strong internal consistency (Nunnally & Bernstein, 1994).

Table 11. AITET Final Validated Structure and Specifications

Component	Factors/Scales	Items	Sample Item	Cronbach's α	Composite Reliability
AI Perceptions	Professional Integration	7	"AI tools help me manage administrative tasks more efficiently"	-	.919
	Teaching & Learning	5	"AI tools enhance my teaching effectiveness"	.872	.860
	Research & Ethics	4	"I can effectively use AI tools for academic writing"	.911	.904
	Learning Design	6	"AI tools help me create better learning materials"	.912	.918
	Ethical Awareness	4	"I am aware of ethical issues in AI use"	.864	.839
Self-Efficacy	AI Implementation Confidence	8	"I feel confident using AI tools in my work"	.945	-
Attitudes	AI Integration Acceptance	8	"I have a positive attitude towards AI in education"	.922	-
Total Scale	-	**26**	**Response Format:** 5-point Likert scale	**Overall α = .967**	-

Note: Final structure includes 26 items after EFA item reduction. Response format: 1 = Strongly Disagree, 5 = Strongly Agree

Administration Protocols and Quality Assurance

Standardised administration guidelines support consistent data collection. The instrument targets higher education teacher educators with a basic familiarity with AI. Recommended sample sizes: ≥100 for descriptive studies; ≥150 for factor analysis (Tabachnick & Fidell, 2019). Ethical clearance, informed consent, and background data on AI training and usage are prerequisites.

Quality assurance procedures encompass three areas: monitoring completion times and flagging responses completed in under three minutes or over thirty minutes; conducting response-pattern checks to identify satisficing behaviour; and tracking internal consistency across samples to ensure reliability is maintained (Huang et al., 2012). These steps ensure data integrity while promoting voluntary and anonymous participation.

Scoring and Interpretation Guidelines

The framework supports both mean-based and sum-score analyses. Interpretation thresholds were developed using percentile-based cut-offs from the validation sample (Cohen et al., 2013). Table 12 details scoring ranges for each construct, categorised into low, moderate, and high readiness levels.

Table 12. AITET Scoring Guide and Interpretation Thresholds

Factor	Item Count	Score Range	Interpretation Thresholds
Professional Integration	7	7-35	Low (7-16), Moderate (17-26), High (27-35)
Teaching & Learning	5	5-25	Low (5-12), Moderate (13-19), High (20-25)
Research & Ethics	4	4-20	Low (4-9), Moderate (10-15), High (16-20)
Learning Design	6	6-30	Low (6-14), Moderate (15-22), High (23-30)
Ethical Awareness	4	4-20	Low (4-9), Moderate (10-15), High (16-20)
Self-Efficacy	8	8-40	Low (8-18), Moderate (19-29), High (30-40)
Attitudes	8	8-40	Low (8-18), Moderate (19-29), High (30-40)

Note: Thresholds based on empirical distribution from validation sample (N=114) using established percentile-based cut-off procedures (Cohen et al., 2013)

Researchers can calculate either domain-specific or composite readiness indices based on the study's scope. This flexibility facilitates cross-sectional benchmarking or longitudinal tracking of AI integration readiness.

Normative Benchmarks and Reference Standards

Normative data (see Table 13) from the validation sample (N = 114) enable the contextualisation of scores. Readiness was highest in *Attitudes* (M = 33.0) and *Professional Integration* (M = 27.8), with moderate performance in *Ethical Awareness* (M = 16.2) and *Research & Ethics* (M = 15.2).

Table 13. Normative Data from Validation Sample (N=114)

Construct	Mean	SD	25th Percentile	50th Percentile	75th Percentile
Professional Integration	27.8	4.2	25.0	28.0	31.0
Teaching & Learning	19.1	3.1	17.0	19.0	21.0
Research & Ethics	15.2	2.8	13.0	15.0	17.0
Learning Design	24.1	3.9	21.0	24.0	27.0
Ethical Awareness	16.2	2.5	15.0	16.0	18.0
Self-Efficacy	27.5	7.6	22.0	28.0	33.0
Attitudes	33.0	5.8	29.0	33.0	37.0

Note: Percentiles provide reference points for comparing individual or group scores

These benchmarks help identify strengths and areas for development at both individual and institutional levels, fostering evidence-based decision-making in faculty development.

Research Applications and Contextual Adaptation

The framework supports a wide range of research and institutional applications, including institutional-level readiness assessments, faculty development planning, evaluation of AI training interventions, and comparative research across institutions or countries.

For longitudinal and cross-cultural research, standard adaptation procedures (e.g., back-translation, CFA) are recommended (Brislin, 1970; Milfont & Fischer, 2010). The instrument can be adapted to preserve theoretical fidelity.

Contextual variations are acknowledged. For instance, STEM faculty may score higher in technical readiness, whereas humanities educators may place greater emphasis on ethical awareness. Therefore, interpretation must take into account disciplinary and institutional contexts rather than rely solely on total scores.

Implementation Framework Summary

The AITET framework provides a standardised yet flexible approach to assessing AI readiness in teacher education. With clearly defined specifications, scoring schemes, normative data, and rigorous validation, it facilitates meaningful application across research, policy, and practice. Its design aligns with global calls for structured, evidence-based approaches to AI integration in education, supporting both theoretical advancement and practical implementation.

DISCUSSION

The development and validation of the AI Teacher Education Tool (AITET) represent a significant step in assessing the readiness of teacher educators for AI integration. This study directly addresses the literature gap concerning the lack of comprehensive, theory-based instruments for this purpose (Granić & Marangunić, 2019; Salas-Pilco et al., 2022).

Theoretical Contributions and Factor Structure

Exploratory factor analysis revealed a robust five-factor structure that reflects the multidimensionality of AI integration. The five domains—*Professional Integration*, *Teaching and Learning Applications*, *Research and Ethical Considerations*, *Learning Design*, and *Ethical Awareness*—align with the frameworks advocated by Celik et al. (2022) and Ng et al. (2023).

The emergence of two distinct ethical constructs supports recent scholarship on the centrality of ethics in AI (Holmes et al., 2022; Foltynek et al., 2023) and validates Choi et al.'s (2023) focus on trust. The explained variance (70.998%) surpasses conventional benchmarks, reinforcing instrument comprehensiveness.

The five-factor structure merits deeper theoretical consideration. The emergence of Professional Integration and Administrative Utility as the largest factor reflects a dimension of AI readiness that most existing instruments overlook, namely the administrative and institutional dimensions of an educator's role. Teacher educators are not only classroom practitioners but also curriculum designers, researchers, and institutional administrators, and the prominence of this factor suggests that AI readiness in professional contexts extends well beyond pedagogical application. The Teaching and Learning Applications factor aligns with the perceived usefulness construct central to TAM (Davis, 1989), confirming that instructional utility remains a primary driver of AI engagement. The Learning Design and Content Creation factor captures a distinctly creative dimension of AI use that has received limited attention in prior measurement work, reflecting the growing role of generative AI in curriculum development. Collectively, the five factors map onto the full breadth of a teacher educator's professional identity rather than a narrow subset of technical competencies, which distinguishes the AITET from earlier instruments focused primarily on classroom technology acceptance.

Psychometric Strength and Validation

The AITET showed excellent reliability (α = .967) and strong subscale consistency (α = .864–.919), meeting established standards (Nunnally & Bernstein, 1994; Scherer et al., 2019). Confirmatory factor analysis supported the model on absolute fit indices (χ^2/df = 1.97; SRMR = .065), though incremental indices CFI (.876) and TLI (.861) fell marginally below the conventional .90 threshold, and RMSEA (.092) exceeded the preferred .08 criterion, indicating modest room for refinement. Three factors likely contribute to this pattern. First, the sample size of 114 participants, though adequate for EFA, is below the recommended threshold of 200 for stable CFA parameter estimation (Kline, 2016), and incremental fit indices such as CFI and TLI are known to be sensitive to sample size, with smaller samples tending to produce lower values even when the underlying model is sound (Hair et al., 2019). Second, some degree of item overlap is anticipated given the conceptually proximate nature of the five factors, particularly between Learning Design and Research and Ethics, which share the highest inter-factor correlation (r = .832). Such conceptual proximity naturally elevates residual covariances and moderately depresses incremental fit. Third, the complexity of measuring AI integration readiness across five professional domains within a single instrument introduces measurement demands that inherently challenge parsimonious model fit, a pattern consistent with research on multidimensional constructs in educational technology contexts (Pfitzner-Eden, 2016). Notwithstanding these limitations, the strong factor loadings, acceptable absolute fit, and comprehensive validity evidence collectively support the instrument's construct validity for its intended purpose.

Convergent validity was confirmed across all factors (*AVE* = .555–.701), with *Research and Ethics* showing the strongest performance (*AVE* = .701; loadings: .812–.867), reinforcing the importance of integrity in AI education (Foltynek et al., 2023).

Compared with existing AI readiness instruments, the AITET offers several distinctive features. Chiu's (2024) TAICS scale addresses six competency dimensions but focuses primarily on self-efficacy rather than perceptions across professional domains. Ramazanoglu and Akin's (2024) RAIS addresses three dimensions, i.e., technology self-efficacy, student interaction, and ethical awareness, and has a narrower scope than AITET's five-factor structure. Chai et al.'s (2024) AILIS was developed for student populations and incorporates the Theory of Planned Behaviour, making it theoretically distinct from the present instrument's TAM and self-efficacy foundations. The AITET's most significant distinguishing feature is the separation of ethical considerations into two empirically distinct constructs: Research and Ethical Considerations, which captures integrity concerns within scholarly practice, and Ethical Awareness and Policy Dimensions, which addresses institutional policy and responsible AI governance. This separation, supported empirically by the EFA and confirmed by acceptable discriminant validity in the CFA, reflects a theoretically meaningful distinction between micro-level ethical practice and macro-level policy awareness, a distinction that existing single-construct ethical measures do not capture.

Practical Implications

The AITET provides diagnostic insights into professional development needs, aligning with Ng et al.'s (2021) call for AI literacy that spans technical, pedagogical, and ethical domains. It enables evidence-based decisions and targeted interventions beyond general digital training (Salas-Pilco et al., 2022).

Normative findings highlight high readiness in *Attitudes* and *Professional Integration*, with moderate scores in *Ethical Awareness* and *Research and Ethics*, indicating areas that require focused support.

Model Extension and Ethical Readiness

This research supports extending the Technology Acceptance Model (TAM) with self-efficacy theory (Bandura, 1997; Pfitzner-Eden, 2016), integrating trust and ethics, and confirms the theoretical propositions of Choi et al. (2023) and Holmes et al. (2022).

The dual ethical constructs encompass both policy awareness and academic integrity, emphasising the necessity for differentiated development strategies (Foltynek et al., 2023).

Limitations and Future Directions

Several limitations of the present study warrant acknowledgement. The sample is geographically restricted to Northern India, which limits the generalisability of findings to other cultural, linguistic, and institutional contexts (Scherer et al., 2019). Although steps were taken to address sampling bias through demographic verification, the purposive selection of institutions based on AI engagement may have produced a sample with higher baseline AI familiarity than the broader teacher educator population, potentially inflating readiness scores. The instrument relies entirely on self-reported perceptions, which are subject to social desirability bias and may not accurately reflect actual AI integration behaviours in practice. The cross-sectional design precludes any assessment of temporal stability or change in AI readiness, limiting understanding of how perceptions evolve in response to professional development or technological change. Additionally, the study does not establish external criterion validity, as AITET scores were not correlated with observable indicators of AI adoption behaviour, institutional AI usage records, or performance outcomes. Formal expert panel content validation was not conducted during this phase, representing a procedural limitation that future studies should address. These limitations collectively point to a clear agenda for subsequent validation work, including longitudinal designs, cross-cultural adaptation, expert review panels, and criterion validity studies linking AITET scores to measurable AI integration outcomes (Milfont & Fischer, 2010).

Several directions for future research emerge from the present study. Cross-cultural validation of the AITET represents the most immediate priority, with studies across diverse geographic, linguistic, and institutional contexts needed to establish measurement invariance and assess the generalisability of the five-factor structure (Milfont & Fischer, 2010). Longitudinal studies tracking AI readiness development over time would provide valuable insight into how teacher educators' perceptions, self-efficacy, and attitudes evolve in response to professional development interventions, institutional policy changes, and broader technological shifts. Comparative studies across academic disciplines would help establish whether the factor structure holds equivalently for STEM and humanities educators, given theoretical expectations of differential readiness profiles across these groups. Importantly, future research should investigate the relationship between AITET scores and actual AI usage behaviour in teaching, research, and administrative practice, providing the external criterion validity evidence that the present study was unable to establish. Expert panel content validation should also be incorporated into future development phases to strengthen the instrument's evidence base for content validity. Finally, developing an abbreviated version of the AITET for use in large-scale institutional surveys and time-constrained research contexts would enhance the instrument's practical utility without compromising its theoretical comprehensiveness.

CONCLUSIONS

This study developed and validated the AI Teacher Education Tool (AITET), a reliable and multidimensional instrument that assesses teacher educators' readiness for AI. The five-factor structure and strong psychometric properties ($\alpha = .967$) confirm its value in both research and institutional contexts.

The tool enhances existing models by integrating TAM, self-efficacy theory, and AI-specific concepts such as trust and ethics. It enables institutions to identify readiness gaps, guide professional development, and support AI integration through evidence-based planning.

The implementation framework and normative data underpin consistent application. Future research should validate the instrument across cultures, assess longitudinal stability, and connect AITET scores with behavioural outcomes. Abbreviated versions may facilitate broader application.

In the context of rapid educational change, tools such as AITET are crucial for ensuring that teacher educators are prepared to embrace AI responsibly, ethically, and effectively.

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