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Psychometric validation of the AI academic phobia scale for pre-service teachers: A confirmatory factor analysis

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Abstract

The increasing integration of artificial intelligence into education has created new opportunities for teaching and learning while introducing psychological challenges that may influence AI adoption among future educators. This study aimed to develop and psychometrically validate the AI Academic Phobia Scale, a multidimensional instrument designed to assess AI-related psychological responses among pre-service teachers. A quantitative cross-sectional survey was conducted with pre-service teachers from teacher education institutions in India. The scale was developed using a systematic psychometric approach that included theory-driven item generation, expert review, face validation, exploratory factor analysis, confirmatory factor analysis, and comprehensive assessments of reliability and validity. The findings supported a four-dimensional structure comprising Learning Anxiety, Professional Threat Fear, Ethical and Privacy Concern, and Low AI Self-Efficacy. The confirmatory analysis supported the measurement model, with a satisfactory overall fit. Reliability and validity were supported through internal consistency, composite reliability, convergent validity, and discriminant validity procedures. The findings demonstrate that the scale is a reliable and valid instrument for assessing AI-related psychological barriers among pre-service teachers. For teacher education institutions, the instrument serves as a practical diagnostic tool to identify readiness gaps before designing AI-focused professional development. For curriculum developers, it provides an evidence base to embed AI literacy, ethical reasoning, and data privacy content into teacher preparation programs. For researchers and policymakers, it offers a validated measure to track AI readiness over time and across institutional and cultural contexts, aligned with national and international priorities for digital transformation in education.

Keywords: Artificial intelligence in education; AI academic phobia; Confirmatory factor analysis; Exploratory factor analysis; Pre-service teachers; Psychometric validation; Scale development

1. Introduction

Artificial intelligence [AI] has rapidly reshaped educational practice across teaching, learning, assessment, and academic and institutional decision-making (Ajani et al., 2025; Zawacki-Richter et al., 2019). The emergence of generative AI applications, particularly large language models such as ChatGPT, has accelerated this transformation by extending opportunities for personalized learning, tutoring-like support, feedback and assessment, and instructional and lesson planning (Kasneci et al., 2023; Opesemowo & Ndlovu, 2024; Yanar & Ergene, 2025). Despite these educational affordances, concerns regarding ethics, privacy and data protection, academic integrity and misuse, algorithmic bias, transparency, and the evolving role of teachers continue to shape the responsible acceptance and implementation of AI in educational settings (Acuyo Cespedes, 2025; Kasneci et al., 2023; Sarıtiken, 2024; Zawacki-Richter et al., 2019).

Teacher education institutions are central to preparing future teachers to use AI effectively, pedagogically, and responsibly, particularly by integrating AI literacy into teacher preparation and providing appropriate institutional support (Chan, 2023). Pre-service teachers therefore require preparation that combines AI literacy, technopedagogical competence, ethical judgment, and opportunities for hands-on experience that can strengthen confidence and readiness to use AI-supported practices (Celik, 2023; Gürbüz et al., 2026; Tsiani et al., 2025). AI readiness is multidimensional, with technological-pedagogical knowledge and self-efficacy associated with adoption intentions, while perceived usefulness, technology self-efficacy, and emotional and psychological factors are related to readiness for AI-integrated pedagogical design (Ismaniati et al., 2025; Tusyanah et al., 2026). Professional identity may also form part of this preparation, as AI-supported practicum experiences can contribute to how pre-service teachers understand pedagogical decision-making and their developing roles as teachers (Danişman, 2026). At the same time, insufficient readiness, low AI literacy, uncertainty about AI reliability, and ethical concerns can constrain educational integration (Akgun & Greenhow, 2022; Pratiwi et al., 2025; Tsiani et al., 2025). Psychological factors should, however, be interpreted cautiously, as emotional factors can shape AI readiness, whereas technostress does not necessarily translate into lower AI acceptance (Çakır & Güner, 2026; Tusyanah et al., 2026).

A small number of instruments have attempted to capture AI-related psychological responses more broadly. Wang and Wang (2022) developed an Artificial Intelligence Anxiety Scale for general and student populations, and this instrument has since been adapted and examined for reliability generalization across different cultural and linguistic contexts (Akkaya et al., 2021; Yıldırım et al., 2026). These efforts confirm that AI-related anxiety is measurable and psychometrically tractable, and they represent an important foundation for the present study.

However, such instruments were designed for general populations rather than pre-service teachers specifically, and they typically capture a narrower construct than the combination of learning-related, professional, ethical, and confidence-related concerns that are unique to teacher preparation. Pre-service teachers occupy a distinctive position: they are simultaneously learners acquiring new technological competence and future professionals responsible for using AI ethically and effectively in their own classrooms. This dual role means that generic AI-anxiety measures may not adequately capture the full range of psychological barriers relevant to this population.

This study introduces AI Academic Phobia as a non-clinical educational construct describing apprehension toward learning and using AI in teacher education contexts. It is characterized by Learning Anxiety [LA], Professional Threat Fear [PT], Ethical and Privacy Concern [EP], and Low AI Self-Efficacy [SE]. These dimensions may influence pre-service teachers' preparedness to integrate AI into future practice.

1.1. Research Gap

Although previous studies have examined AI anxiety, technology anxiety, computer anxiety, technology acceptance, and AI readiness, existing instruments primarily focus on general populations or isolated psychological constructs. None provides a psychometrically validated multidimensional instrument specifically designed to assess AI-related psychological barriers among pre-service teachers by integrating LA, PT, EP, and SE. Consequently, teacher education institutions lack a context-specific tool to identify and address the psychological factors that may influence future teachers' readiness to adopt AI in educational practice.

1.2. Aim of the Study

To address this research gap, the present study aimed to develop and psychometrically validate the AAPS for pre-service teachers using established scale development procedures, including expert validation, EFA, CFA, and comprehensive assessments of reliability and validity.

2. Literature Review

The absence of a validated, teacher-education-specific instrument matters because psychological readiness, not only technical skill, is likely to shape how future teachers engage with AI in their own classrooms. A pre-service teacher who is technically capable of using an AI tool may still avoid it because of anxiety about learning to use it, fear that it threatens their professional identity, concern about its ethical implications, or a simple lack of confidence in their ability to use it well. Existing general-population AI-anxiety scales were not designed to distinguish between these sources of resistance, which means institutions currently have no way to diagnose which specific barrier is driving low AI adoption among their trainees, or to target professional development accordingly. Addressing this gap is therefore both a measurement problem and a practical one for teacher education programs seeking to prepare confident, AI-ready educators.

AI has become a transformative force in education, with generative tools such as ChatGPT expanding opportunities for personalized learning, intelligent tutoring, automated assessment, and curriculum design (Kashif et al., 2025; Uygun, 2024). Zawacki-Richter et al. (2019) observe that while AI enhances learning experiences, it simultaneously introduces challenges related to ethics, transparency, privacy, and the evolving role of educators, highlighting the need for teacher education programs to prepare future educators for AI-integrated environments.

Successful AI integration depends on teachers' readiness and professional knowledge for pedagogically and ethically appropriate use of AI-supported practices (Celik, 2023; Gürbüz et al., 2026; Tusyanah et al., 2026). AI literacy encompasses awareness, use, critical evaluation, and ethical considerations and, in teacher education, extends beyond technical familiarity to pedagogical judgment and responsible use (Danişman & Evran Acar, 2026; Sari et al., 2025). However, pre-service teachers' practical engagement with AI can remain uneven, and readiness appears to involve cognitive, skill-based, perceptual, and affective dimensions rather than technical competence alone (Gürbüz et al., 2026; Tusyanah et al., 2026). AI-related anxiety also encompasses learning-related concerns and fears of job replacement (Akkaya et al., 2021). Among educators, additional concerns include reliability, privacy and data protection, and algorithmic bias, highlighting the need for ethically informed and critically reflective AI integration (Opesemowo & Ndlovu, 2024; Sarıtiken, 2024).

Three theoretical perspectives inform the present study. Bandura's (1977) Self-Efficacy Theory posits that low confidence contributes to avoidance and anxiety, grounding the SE dimension. Davis's (1989) Technology Acceptance Model explains adoption through perceived usefulness and ease of use, while Venkatesh et al.'s (2003) Unified Theory of Acceptance and Use of Technology [UTAUT] extends this by incorporating performance expectancy, social influence, and institutional support. Together, these frameworks provide the conceptual basis for understanding AI Academic Phobia as a multidimensional educational construct encompassing LA, PT, EP, and SE.

Scale development requires systematic psychometric procedures. Clark and Watson (1995) recommend beginning with clear theoretical definitions followed by expert review; DeVellis (2017) advocates iterative item refinement; Boateng et al. (2018) propose structured EFA–CFA sequencing; and Worthington and Whittaker (2006) specifically recommend EFA before CFA using independent samples. Although prior research has examined AI anxiety, technology acceptance, and AI readiness, no existing instrument specifically captures the multidimensional psychological barriers among pre-service teachers. The AAPS addresses this gap by integrating LA, PT, EP and SE into a unified, psychometrically validated framework specifically calibrated to the pre-service teacher population, following the same sequential EFA-CFA logic recommended in previous methodological work (Boateng et al., 2018; Worthington & Whittaker, 2006).

3. Method

3.1. Research Design

The present study employed a quantitative, cross-sectional survey design to develop and validate the AAPS in accordance with established psychometric guidelines (Boateng et al., 2018). The validation process comprised six sequential stages: (1) item generation, (2) expert validation, (3) face validation and pilot testing, (4) EFA, (5) CFA and (6) reliability and validity assessment.

3.2. Participants and Sampling

The study was conducted among 1,592 pre-service teachers enrolled in teacher education institutions across India. Participants were selected using a simple random sampling technique to obtain a representative sample from diverse teacher education institutions. The sample size exceeded the recommended minimum requirements for both EFA and CFA, thereby providing adequate statistical power for psychometric validation. The participants represented diverse demographic backgrounds. Of the total respondents, 1,381 (86.74%) were female, and 211 (13.25%)

were male. Regarding residence, 839 (52.70%) participants were from rural areas, 662 (41.58%) from urban areas, and 91 (5.71%) from semi-urban areas. The sample included respondents from different types of teacher education institutions, comprising 523 (32.85%) from government institutions, 484 (30.40%) from aided institutions, and 585 (36.74%) from private institutions. Regarding the medium of instruction, 865 (54.33%) participants studied at English-medium institutions, whereas 727 (45.66%) were enrolled in regional language institutions. These characteristics indicate that the sample reflects a diverse range of educational and demographic backgrounds within the Indian teacher education context.

3.3. Instrument Development

The AAPS was developed through a theory-driven process based on an extensive review of the literature on artificial intelligence in education, AI anxiety, teacher readiness, self-efficacy, and technology acceptance. Item development began with an explicit operational definition of each of the four proposed dimensions so that item writing could proceed from a shared conceptual anchor rather than from loosely related ideas about AI-related discomfort. LA was defined as apprehension and worry associated with the demands of acquiring new AI-related knowledge and skills. PT was defined as concern that AI may displace, devalue, or otherwise threaten the teaching profession and the pre-service teacher's professional identity. EP was defined as apprehension regarding data privacy, algorithmic bias, academic integrity, and the broader ethical implications of AI use in educational settings. SE was defined as a lack of confidence in one's ability to understand, operate, and use AI tools productively in academic and professional contexts.

Using these operational definitions, an initial pool of 18 items was generated, distributed as evenly as possible across the four dimensions. Items were written in simple, jargon-free language appropriate for pre-service teachers, avoiding double-barreled statements and closely mirroring the wording conventions used in established scales of anxiety, self-efficacy, and technology acceptance. All items were measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), with higher scores indicating greater levels of AI-related psychological barriers. This initial 18-item pool underwent expert content validation, as described in the following section.

3.4. Content and Face Validity

Six experts in teacher education, educational technology, educational psychology, and psychometrics evaluated the initial 18-item instrument for relevance, clarity, representativeness, and appropriateness. Based on expert recommendations, two items were removed as redundant or insufficiently representative of the intended constructs. The revised 16-item version (See Appendix 1) demonstrated excellent content validity (Scale-Level Content Validity Index [S-CVI] = .91). It was subsequently subjected to face validation with a small group of pre-service teachers before large-scale data collection.

3.5. Data Analysis

Data were analyzed in three sequential stages, each conducted using a separate, randomly split subsample where appropriate. First, EFA was conducted on the first subsample to examine the underlying factor structure of the retained items. Sampling adequacy was evaluated using Bartlett's Test of Sphericity and the Kaiser-Meyer-Olkin [KMO] (Kaiser, 1974) measure of sampling adequacy. Factors were extracted using the minimum residual method with oblimin (oblique) rotation, given the expected correlations among the underlying constructs, and the number of factors to retain was determined using eigenvalues, the scree plot, and Horn's parallel analysis.

Second, CFA was conducted using JASP with Maximum Likelihood Estimation to verify the four-factor measurement model identified during the exploratory phase. Model fit was evaluated using the ratio of chi-square to degrees of freedom (CMIN/DF), the Comparative Fit Index [CFI], the Tucker-Lewis Index [TLI], the Root Mean Square Error of Approximation [RMSEA], and the Standardized Root Mean Square Residual [SRMR], interpreted according to established guidelines (Hu & Bentler, 1999; Kline, 2016).

Third, reliability and validity were assessed. Internal consistency was evaluated using Cronbach's alpha and Composite Reliability [CR]. Convergent validity was assessed using Average Variance Extracted [AVE], and discriminant validity was evaluated using the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio [HTMT] (Henseler et al., 2015). Item-level contribution to each construct was examined using corrected item-total correlations.

4. Results

4.1. Item Development Process

Table 1 presents the systematic stages followed in developing the AI Academic Phobia Scale, beginning with item generation and culminating in the final validated instrument. The table summarizes the refinement process undertaken to ensure the scale's content validity and conceptual clarity.

Table 1

Item Development Process

Stage	*Number of Items*	*Outcome*
Literature Review	18	Initial item pool
Expert Validation	16	Final instrument
EFA	16	Four-factor structure confirmed
CFA	16	Measurement model validated

The scale development process proceeded through four stages, moving from an initial pool of 18 items to a final, psychometrically confirmed 16-item instrument. Two items were removed at the expert validation stage as redundant or insufficiently representative of their intended construct, while no further items were removed during either the EFA or the CFA stage. This indicates that the four-factor structure proposed on theoretical grounds was well supported empirically from an early stage, requiring refinement only at the expert-review step rather than through data-driven item deletion during the factor-analytic stages.

4.2. Exploratory Factor Analysis

Table 2 presents the factor loadings and communalities obtained from the EFA.

Table 2

Factor Loadings and Communalities

Item	*Factor 1(PT)*	*Factor 2(SE)*	*Factor 3(LA)*	*Factor 4(EP)*	h^2
LA1			.690		.510
LA2			.811		.384
LA3			.742		.425
LA4			.554		.583
PT1	.732				.496
PT2	.766				.422
PT3	.685				.494
PT4	.604				.513
EP1				.595	.460
EP2				.750	.425
EP3				.844	.348
EP4				.469	.572
SE1		.578			.602
SE2		.756			.420
SE3		.711			.504
SE4		.728			.460
SS Loadings	2.187	2.099	2.054	2.041	
% Variance	13.67	13.12	12.84	12.76	
Cumulative %	13.67	26.79	39.63	52.38	

Note. Extraction method: minimum residual. Rotation method: oblimin. Factor loadings < .30 suppressed for clarity. h^2 = communality. PT = Professional Threat Fear; SE = Low AI Self-Efficacy; LA = Learning Anxiety; EP = Ethical and Privacy Concern.

Table 2 illustrates each item's contribution to the four underlying dimensions of the AAPS and supports the proposed factor structure. Before conducting the EFA, the suitability of the data for factor analysis was assessed. Bartlett's test of sphericity was significant, $\chi^2(120) = 9688.90$, $p < .001$, indicating sufficient correlation among items to proceed with factor analysis. The KMO measure of sampling adequacy was .899, well above the recommended minimum of .60, and item-level MSA values ranged from .845 to .935, confirming adequate sampling adequacy. Factors were extracted using the minimum residual method with oblimin rotation, appropriate given the expected correlations among the underlying constructs. The number of factors to retain was determined by inspecting eigenvalues and the scree plot against a parallel analysis of simulated data; four factors emerged above the simulated eigenvalue threshold, consistent with the theoretical four-dimensional structure of the scale. The four-factor solution demonstrated a clean, simple structure in which every item loaded saliently on only one factor with no meaningful cross-loadings, providing evidence of good discriminant validity between factors. Factor loadings ranged from .469 to .844, with most exceeding the recommended .50 benchmark, and communalities ranged from .348 to .602, indicating that approximately 35% to 60% of each item's variance was explained by the retained factors. The four factors jointly explained 52.38% of the total variance, with each contributing a comparable share ranging from 12.76% to 13.67%, suggesting that all four dimensions are of relatively equal importance within the construct. These results provide strong empirical support for the proposed four-factor structure of the AAPS.

4.3. Sampling Adequacy and Model Fit for EFA

Table 3 presents the results of the sampling adequacy tests and model fit indices for the EFA. These statistics were examined to assess the suitability of the data for factor extraction and the adequacy of the exploratory measurement model.

Table 3

Tests of Sampling Adequacy and Model Fit for EFA

Test/Index	*Value*	*df*	*p*
Bartlett's Test of Sphericity	χ^2 = 9688.90	120	< .001
Kaiser-Meyer-Olkin (KMO)	.899	—	—
Model χ^2	186.84	62	< .001
RMSEA [90% CI]	.036 [.030, .041]	—	—
TLI	.975	—	—
BIC	−270.27	—	—

Note. RMSEA = root mean square error of approximation; TLI = Tucker-Lewis Index; BIC = Bayesian Information Criterion. Extraction method: minimum residual; rotation method: oblimin.

The sampling adequacy test, as indicated by the KMO value of .899, falls in the "marvelous" range (Kaiser, 1974), and Bartlett's test was highly significant, confirming that the correlation matrix was factorable. The four-factor solution showed a clean, simple structure – every item loaded saliently (≥ .47) on only one factor, with no meaningful cross-loadings, supporting good discriminant validity between factors. Loadings ranged from .469 (EP4) to .844 (EP3), with the majority exceeding the common .50 benchmark for a "good" loading. Communalities ranged from .348 (SE1) to .602 (EP3), meaning between roughly 40% and 65% of each item's variance was explained by the four-factor solution. Most items had communalities above .45, indicating adequate shared variance; SE1 (.398) and LA4 (.417) were comparatively weaker and could be flagged for review in future scale refinement. The four factors jointly explained 52.38% of the total variance, with each factor contributing a fairly even share (~12.8%–13.7%), suggesting that the four dimensions are of comparable relative importance/strength within the measured construct. Model fit indices such as RMSEA (.036; 90% CI (.030, .041) indicate a close fit (values < .05 are considered good; (Hu & Bentler, 1999), and TLI (.975) exceeds the .95 threshold for a good fit. Although the χ^2 test was significant (which is common and less informative in large samples), the overall pattern of fit indices supports the four-factor model as an acceptable representation of the data.

4.4. Standardized Factor Loadings

Table 4 presents the standardized factor loadings obtained from the CFA. The table demonstrates the relationships between the observed items and their respective latent constructs in the proposed measurement model.

Table 4
Standardized Factor Loadings

Constructs	*SFL*	*M*	*SD*	*t*	*p*	*CI*
Ethical and Privacy Concern						
EP1 ← EP	.745	.747	0.017	43.431	< .001	[.711, .781]
EP2 ← EP	.747	.748	0.018	41.857	< .001	[.709, .781]
EP3 ← EP	.760	.760	0.020	38.766	< .001	[.718, .798]
EP4 ← EP	.663	.663	0.021	31.212	< .001	[.618, .704]
Learning Anxiety						
LA1 ← LA	.701	.700	0.021	32.770	< .001	[.660, .740]
LA2 ← LA	.764	.763	0.018	41.312	< .001	[.728, .800]
LA3 ← LA	.760	.761	0.017	44.341	< .001	[.727, .792]
LA4 ← LA	.652	.652	0.025	26.061	< .001	[.599, .699]
Professional Threat Fear						
PT1 ← PT	.694	.694	0.020	34.282	< .001	[.652, .733]
PT2 ← PT	.753	.754	0.016	46.024	< .001	[.718, .783]
PT3 ← PT	.709	.709	0.020	35.954	< .001	[.669, .746]
PT4 ← PT	.711	.711	0.019	36.933	< .001	[.674, .747]
Self-Efficacy						
SE1 ← SE	.635	.635	0.024	25.938	< .001	[.585, .680]
SE2 ← SE	.746	.747	0.020	38.227	< .001	[.707, .785]
SE3 ← SE	.704	.703	0.021	33.448	< .001	[.662, .743]
SE4 ← SE	.735	.734	0.021	34.613	< .001	[.692, .773]

Note. SFL: Standardized factor loading.

The factor loadings for all items across the four constructs: EP, LA, PT, and SE. All items were statistically significant ($p < .001$), indicating that each item is properly aligned with its intended construct. For EP, loadings ranged from .663 (EP4) to .760 (EP3). For LA, loadings ranged from .652 (LA4) to .764 (LA2). For PT, loadings ranged from .694 (PT1) to .753 (PT2). For SE, loadings ranged from 0.635 (SE1) to .746 (SE2). All loadings exceeded the acceptable threshold of .60, with many above .70, indicating strong item-construct relationships. The t-values ranged from 25.938 to 46.024, well above the critical value of 1.96, confirming statistical significance. The confidence intervals did not include zero, further supporting the stability of these estimates. Overall, the results demonstrate that all items are well aligned with their respective constructs and that the measurement model is acceptable

4.5. Model Fit Indices

Table 5 presents the model fit indices obtained from the CFA. These indices were examined to evaluate the overall fit of the proposed four-factor measurement model to the observed data. The model fit indices for the four-factor CFA model. The model fit indices indicated that the four-factor model fit the data well. The chi-square value was 385.327 (df = 98, $p < .001$). Because chi-square is sensitive to large sample sizes, the CMIN/DF ratio was examined instead. The CMIN/DF value was 3.932, below the recommended threshold of 5, indicating a good fit (Bentler, 1990; Consiglio et al., 2013). The RMSEA value was .043, below the cutoff of .08, suggesting a close fit (Hu & Bentler, 1999; Steiger, 2007). The 90% confidence interval ranged from .038 to .047, remaining within the acceptable range. The GFI (.971) and AGFI (.960) exceeded the required levels, indicating excellent model fit (Hair et al., 2010; Tanaka & Huba, 1985). The PGFI value was .700, above the .50 threshold, reflecting good model parsimony (Mulaik et al., 1989). The SRMR value was .033, well below the 0.08 cutoff, indicating a very good fit (Hu & Bentler, 1999). The NFI value was .960, exceeding the acceptable level of .80 (Hooper et al., 2008). The TLI (.963) and CFI (.970) values both

Table 5
Model Fit Indices

Fit Index Measure	*Estimated model value*	*Threshold Value*	*Reference*	*Interpretation*
Chi-square	385.327	–	–	–
Model parameters, n	38	–	–	–
Observations, n	1,592	–	–	–
df	98	–	–	–
p-value	< .001	–	–	–
CMIN/DF	3.932	< 5	(Bentler, 1990; Consiglio et al., 2013)	Good fit
RMSEA	.043	< .08	(Hu & Bentler, 1999; Steiger, 2007)	Good fit
RMSEA Low 90% CI	.038	–	–	–
RMSEA High 90% CI	.047	–	–	–
GFI	.971	> .90	(Hair et al., 2010; Tanaka & Huba, 1985)	Good
AGFI	.960	> .80	(Gefen et al., 2003)	Good
PGFI	.700	≥ .50	(Kelloway, 1998; Mulaik et al., 1989; Sharma, 1995)	Good
SRMR	.033	< .08	(Hu & Bentler, 1999)	Good
NFI	.960	> .80	(Hooper et al., 2008)	Good
TLI	.963	> .95	–	Good
CFI	.970	> .90	(Bentler, 1990)	Good
AIC	461.327	–	–	–
BIC	665.491	–	–	–

exceeded their recommended thresholds, indicating a strong model fit (Bentler, 1990; Hu & Bentler, 1999). Overall, all fit indices met the recommended criteria, confirming that the proposed four-factor model provides a good fit to the data.

4.6. Reliability Analysis

Table 6 presents the internal consistency estimates for each construct of the AAPS. The reliability coefficients were examined to assess the consistency of the items measuring each latent dimension.

Table 6
Internal Consistency and Inter-Construct Correlations

Constructs	*Items*	*Α*	*EP*	*LA*	*PT*	*SE*
EP	4	.817	1.00	.303	.690	.511
LA	4	.809	—	1.00	.389	.559
PT	4	.808	—	—	1.00	.480
SE	4	.797	—	—	—	1.00

The reliability estimates and inter-construct correlations for the four factors. Cronbach's alpha values were 0.817 for EP(EP), .809 for LA, .808 for PT, and 0.797 for SE. All values exceeded the recommended threshold of .70, indicating good internal consistency for each construct. This suggests that the items within each factor reliably measure the same underlying concept. The inter-factor correlations were all positive. EP showed moderate correlations with PT (r = .690), SE (r = .511), and LA (r = .303). LA was moderately related to SE (r = .559) and PT (r = .389). PT and SE also exhibited a moderate relationship (r = .480). All correlations were positive, confirming that the constructs are related. Importantly, none of the correlation values were excessively high, indicating that each construct captures a distinct aspect of AI academic phobia rather than overlapping with others. Overall, these findings confirm that the AAPS is reliable and that its four dimensions are related yet distinguishable.

4.7. Corrected Item–Total Correlations

Table 7 presents the corrected item–total correlations for the retained items of the AI Academic Phobia Scale. These values were examined to assess each item's contribution to its respective construct and to inform item retention decisions.

Table 7
Corrected Item–Total Correlations

Construct and Item	*Corrected Item–Total Correlation*	*Decision*
Learning Anxiety		
LA1	.651	Retain
LA2	.712	Retain
LA3	.702	Retain
LA4	.618	Retain
Professional Threat Fear		
PT1	.675	Retain
PT2	.711	Retain
PT3	.682	Retain
PT4	.661	Retain
Ethical and Privacy Concern		
EP1	.706	Retain
EP2	.727	Retain
EP3	.750	Retain
EP4	.648	Retain
Self-Efficacy		
SE1	.624	Retain
SE2	.697	Retain
SE3	.676	Retain
SE4	.693	Retain

The corrected item–total correlations ranged from .618 to .750 across all four dimensions, exceeding the recommended minimum threshold of .30 (DeVellis, 2017). Within the LA dimension, correlations ranged from .618 to .712, indicating that all four items contribute meaningfully to the construct. For PT, values ranged from .661 to .711, reflecting consistent and adequate item-level associations. The EP dimension demonstrated the strongest overall item contributions, with correlations ranging from .648 to .750, suggesting that these items are particularly well aligned with their intended construct. For SE, correlations ranged from .624 to .697, confirming satisfactory item-level consistency across the dimension. Since all items exceeded the recommended threshold and no item demonstrated a substantially weaker association relative to others, no additional item removal was considered necessary at this stage of instrument validation. Collectively, these findings confirm that all 16 retained items meaningfully contribute to the internal consistency of their respective dimensions and support retaining the full item set in the final version of the AAPS.

4.8. Convergent Validity and Discriminant Validity

Table 8 presents the results of the convergent and discriminant validity analyses for the proposed measurement model. The table summarizes the evidence supporting the validity of the constructs measured by the AAPS.

Table 8

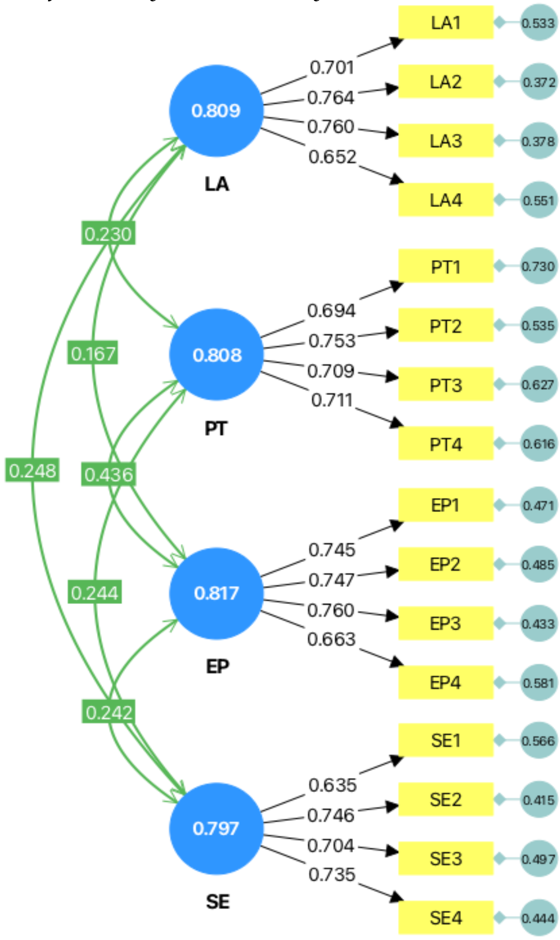
Convergent and Discriminant Validity

Constructs	*Composite Reliability*	*AVE*	*EP*	*LA*	*PT*	*SE*
EP	.820	.533	(.730)			
LA	.810	.519	.303	(.721)		
PT	.808	.514	.690	.389	(.717)	
SE	.799	.502	.511	.559	.480	(.706)

The convergent and discriminant validity estimates for the four constructs using the Fornell-Larcker criterion. Convergent validity was assessed using composite Reliability values and average variance extracted [AVE]. The composite reliability values were .820 (EP), .810 (LA), .808 (PT), and .799 (SE). All exceeded the recommended threshold of 0.70, indicating good reliability (Hair et al., 2010). The AVE values were .533 (EP), .519 (LA), .514 (PT), and .502 (SE). All values exceeded the recommended threshold of 0.50, indicating acceptable convergent validity (Fornell & Larcker, 1981). Discriminant validity was evaluated using the Fornell-Larcker criterion. The diagonal values represent the square roots of the AVEs for each construct: .730 (EP), .721 (LA), .717 (PT), and .706 (SE). Each of these values exceeded the correlations between the respective construct and others. For instance, EP (.730) was higher than its correlations with LA (0.303), PT (.690), and SE (.511). Similarly, LA (.721) was higher than its correlations with PT (.389) and SE (.559). This pattern held for all constructs, indicating that each construct is distinct from the others. Overall, the results confirm that the measurement model demonstrates satisfactory convergent and discriminant validity.

Figure 1 illustrates the validated four-factor measurement model of the AAPS obtained through CFA. The figure depicts the relationships between the latent constructs and their corresponding observed indicators. The CFA measurement model for the four constructs: EP, LA, PT, and SE. All items loaded acceptably onto their respective constructs, with factor loadings ranging from .635 to .764. The highest loading was observed for LA (LA2 = .764), while the lowest loading was for SE (SE1 = .635). Most loadings exceeded .70, indicating strong item-construct relationships. The reliability values for the constructs ranged from .797 to .817. EP showed the highest reliability (.817), and SE showed the lowest (.797), both of which remain acceptable. The relationships among the constructs were all positive and moderate. The strongest relationship was between PT and EP (.436). Other notable relationships included LA with SE (.248), LA with PT (.230), and EP with LA (.167). Overall, Figure 1 illustrates that all constructs are properly connected, reliable, and distinct, further supporting the validity of the four-factor model.

Figure 1
Confirmatory Factor Analysis Measurement Model of the AI Academic Phobia Scale



4.9. Heterotrait–Monotrait Ratio [HTMT]

Table 9 presents the HTMT values for the four constructs of the AAPS. These values were examined to provide additional evidence of discriminant validity by assessing the distinctiveness of the latent constructs.

Table 9
HTMT Ratios

Construct	*LA*	*PT*	*EP*	*SE*
LA	–	.516	.468	.656
PT	.516	–	.777	.610
EP	.468	.777	–	.655
SE	.656	.610	.655	–

All HTMT values remained below the recommended conservative threshold of .85 (Henseler et al., 2015), confirming that all four latent constructs are empirically distinct. The highest value was observed between PT and EP (.777), which is conceptually expected as both dimensions relate to broader concerns about AI's implications for professional roles and societal values. However, this value remains well below the discriminant validity threshold, indicating that while these dimensions are related, they are not redundant. The lowest value was between LA and EP (.468), suggesting these two dimensions are the most distinct from each other. Overall, the HTMT results provide strong evidence that the four constructs measure related but separate aspects of AI Academic Phobia.

5. Discussion

The present study developed and psychometrically validated the AAPS as a multidimensional instrument for assessing AI-related psychological barriers among pre-service teachers. The findings demonstrate that AI Academic Phobia is not a single psychological construct but comprises four interrelated dimensions: LA, PT, EP, and SE. This multidimensional structure supports the view that pre-service teachers' readiness to integrate AI into teaching depends not only on technological competence but also on emotional, ethical, and professional considerations. These findings are consistent with previous research suggesting that teachers' responses to AI are shaped by cognitive, emotional, and professional factors rather than by technical knowledge alone (Chassignol et al., 2018; Chiu et al., 2022). Consequently, teacher education programs should adopt comprehensive approaches that simultaneously develop AI literacy, ethical reasoning, professional confidence, and reflective practice.

The instrument's satisfactory internal consistency indicates that the four dimensions measure distinct aspects of AI Academic Phobia. This suggests that teacher education institutions can use the scale with confidence to identify specific psychological barriers experienced by pre-service teachers before implementing AI-related training programs (Akgun & Greenhow, 2022). Rather than adopting generic interventions, institutions can design targeted support that addresses LA, professional concerns, ethical awareness, or self-efficacy according to identified needs (Boateng et al., 2018; Hair et al., 2021).

The confirmation of the proposed four-factor measurement model also provides empirical support for conceptualizing AI Academic Phobia as a coherent educational construct. The findings extend existing research on AI anxiety by demonstrating that concerns surrounding AI adoption among future teachers are multidimensional and context-specific (Celik, 2023; Yim & Wegerif, 2024). Unlike previous AI anxiety instruments developed primarily for general populations, the AAPS captures psychological dimensions that directly relate to teacher preparation, professional identity, and educational practice. This highlights the importance of considering the unique responsibilities of pre-service teachers when investigating AI readiness in educational settings (Crompton & Burke, 2023).

The observed relationships among the four dimensions further indicate that psychological responses toward AI are interconnected. Concerns about professional identity frequently coexist with EP, suggesting that future teachers evaluate AI not only as a technological innovation but also as a factor that may influence their professional responsibilities and classroom decision-making. This finding reinforces the importance of embedding authentic AI experiences within teacher education programs so that future teachers develop confidence through meaningful engagement rather than through theoretical knowledge alone.

Beyond its psychometric contribution, the validated AAPS provides an important foundation for future educational research. The instrument provides researchers with a context-specific measure to examine relationships between AI Academic Phobia and other educational constructs, including AI literacy, digital competence, technology acceptance, teaching self-efficacy, instructional innovation, and professional identity. The availability of a validated instrument also enables longitudinal studies examining changes in AI readiness following curriculum interventions, institutional initiatives, or professional development programs.

Finally, the present study extends the literature in two significant ways. First, it introduces AI Academic Phobia as a distinct educational construct specifically relevant to pre-service teachers, thereby addressing an important gap in existing AI anxiety research. Second, by integrating Self-Efficacy Theory (Bandura, 1977), the Technology Acceptance Model (Davis, 1989), and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), the study provides a stronger theoretical foundation for understanding psychological readiness for AI adoption in teacher education. The AAPS, therefore, contributes not only a validated measurement instrument but also a conceptual framework that can guide future research and practice in AI-integrated teacher education.

6. Implications

The present study contributes to the growing body of literature on artificial intelligence in education by conceptualizing AI Academic Phobia as a multidimensional educational construct rather than as a general form of technology anxiety. By integrating Self-Efficacy Theory (Bandura, 1977), the Technology Acceptance Model (Davis, 1989) and drawing on the Unified Theory of Acceptance and Use of Technology, the study demonstrates that psychological readiness for AI adoption is shaped by confidence, professional identity, ethical concerns, and perceptions of learning challenges, in addition to perceived usefulness and ease of use (Takona, 2024; Zhai et al., 2021). Furthermore, the rigorous psychometric validation process provides a reliable instrument that future researchers can employ to examine AI readiness across diverse educational contexts, populations, and cultures.

The validated AAPS offers teacher education institutions a practical diagnostic instrument for identifying specific psychological barriers experienced by pre-service teachers before implementing AI-related instructional initiatives (Hamlin et al., 2023; Yıldırım et al., 2026). Rather than providing uniform AI training, teacher educators can design targeted interventions that address specific areas of need, including reducing LA, strengthening AI self-efficacy, addressing concerns about professional identity, and promoting ethical awareness (Akgun & Greenhow, 2022; Albadarin et al., 2024; Kasneci et al., 2023). Curriculum developers may also use the findings to integrate AI literacy, responsible AI practices, data privacy, and algorithmic fairness into teacher education programs in a systematic manner (Kong & Lai, 2022).

From a policy perspective, the AAPS supports national and international initiatives promoting responsible AI integration in education, including the objectives of India's National Education Policy (Ministry of Human Resource Development, 2020). Policymakers may use the instrument to monitor AI readiness across teacher education institutions, evaluate the effectiveness of professional development programs, and inform evidence-based strategies for AI implementation (Wang & Wang, 2022). The scale also enables comparative studies across institutions and countries, thereby supporting international research on teachers' preparedness for AI-enabled education (Levis et al., 2022).

7. Limitations and Future Research

Several limitations should be acknowledged. First, the cross-sectional design precludes conclusions about the stability or development of AI Academic Phobia over time; longitudinal studies are recommended. Second, the sample is drawn from Indian teacher education institutions, which may limit generalizability; future studies should validate the AAPS across diverse cultural and institutional contexts. Third, exclusive reliance on self-report data introduces potential response bias; future research should complement this with qualitative or mixed-method approaches. Fourth, additional validation is needed, including test–retest reliability and criterion-related validity. Finally, measurement invariance across demographic groups was not examined; future studies should test configural, metric, and scalar invariance with respect to gender, specialization, and institutional type.

8. Conclusion

The present study developed and psychometrically validated the AAPS as a context-specific instrument for assessing AI-related psychological barriers among pre-service teachers. Using a systematic process including expert validation, EFA, CFA, and comprehensive reliability and validity assessments, the study established a four-factor model comprising LA, PT, EP, and SE. The findings provide strong psychometric evidence supporting the AAPS through Composite Reliability, AVE, the Fornell–Larcker criterion, HTMT, and corrected item–total correlations. Beyond its psychometric contribution, the study advances the field by conceptualizing AI Academic Phobia as a multidimensional educational construct, demonstrating that effective AI integration depends not only on technological competence but also on educators' confidence, ethical awareness, and perceptions of professional identity. The AAPS provides a scientifically validated instrument to support future research, teacher education programs, and policy initiatives aimed at fostering confident, ethical, and responsible AI integration in education.

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Data availability: The dataset generated and analyzed during the current study is available from the corresponding author upon reasonable request.

Declaration of generative AI: During the preparation of this work, the authors used ChatGPT, Grammarly and Quillbot for language refinement, grammar correction, formatting assistance, and improving clarity of academic writing. After using these tools, the authors carefully reviewed, revised, and validated the entire content and take full responsibility for the originality, accuracy, and integrity of the publication.

Declaration of interest: We are the authors declare that we have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The writing of this paper was carried out together and maintained mutual relations with each other in togetherness, and there was no conflict of interest.

Ethics declaration: Prior administrative permission to conduct the study was obtained from the heads of the participating teacher education institutions before data collection. Participation was voluntary, and informed consent was obtained electronically from all participants before they completed the questionnaire. Participants were informed about the purpose of the study, the voluntary nature of their participation, their right to withdraw at any time without penalty, and the confidentiality and anonymity of their responses. No personally identifiable information was collected, and all data were used exclusively for academic research purposes. The study adhered to the ethical principles governing educational research involving human participants.

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Appendix 1. AI Academic Phobia Scale (AAPS)

Instructions

The following statements assess your perceptions and feelings regarding the use of artificial intelligence (AI) in teaching and learning. There are no right or wrong answers. Please indicate the extent to which you agree with each statement by selecting the most appropriate response.

Response scale. 1 = Strongly Disagree; 2 = Disagree; 3 = Neutral; 4 = Agree; 5 = Strongly Agree.

Table A1

Items and Dimensions of the AI Academic Phobia Scale

Dimension and Item	Statement
Learning Anxiety	
LA1	I feel nervous about learning new AI tools for teaching.
LA2	I find it difficult to learn AI tools for my studies.
LA3	I feel nervous when I am asked to use AI for my coursework.
LA4	I feel uncomfortable when attending AI training programmes.
Professional Threat Fear	
PT1	I fear that AI may replace teaching jobs in the future.
PT2	I worry that AI may reduce the value of my degree.
PT3	I fear that institutions may trust AI more than teachers.
PT4	I feel that AI may reduce creativity in my teaching.
Ethical and Privacy Concern	
EP1	I fear that AI in institutions may violate students' privacy.
EP2	I fear that AI might treat some students unfairly.
EP3	I fear that AI may negatively affect students' emotional well-being.
EP4	I fear that AI may be used to monitor teachers unfairly.
Low AI Self-Efficacy	
SE1	I doubt that I can use AI effectively in my teaching and learning practice.
SE2	I fear that I do not have the necessary skills to use AI for teaching.
SE3	I fear that other students can learn AI faster than me.
SE4	I fear that I cannot manage AI-related problems during teaching.

Note. LA = Learning Anxiety; PT = Professional Threat Fear; EP = Ethical and Privacy Concern; SE = Low AI Self-Efficacy.