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# Artificial Intelligence Competence Teachers' Assessment Scale (AICTS): Development and Validation

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## Abstract

The rapid development in artificial intelligence (AI) is transforming the education system globally. It is pertinent to assess the competence level and teachers' willingness to integrate AI into their professional teaching practice. Although the potential of AI literacy is increasing, the current tools are rather limited in scope and tend to focus on the student population or the general public, disregarding a specific cognitive, attitudinal, and professional skills focus which are required for teachers. This research overcomes this limitation by developing and validating the Artificial Intelligence Competence Teachers Assessment Scale (AICTAS), which is multidimensional in structure and was conceptually designed over three core domains, including Cognitive Competence, Attitudinal Competence, and Professional Competence. The initial scale consisted of 84 Items, which were reduced to 75 after constructing content validity. The 75-item scale was administered to a sample of 390 teachers of various academic disciplines form public and private universities. Exploratory factor analysis (EFA) supported a 13-factor structure, retaining 67 Items that explained 69.54% of the total variance. The structure was confirmed by confirmatory factor analysis (CFA) that provided acceptable fit indices (df: 2; 2.39; RMSEA = 0.060; CFI = 0.818). AITCAS showed great internal consistency (alpha = 0.832), indicative of a reliable instrument. It is recommended to use this validated scale to assess AI competence among teachers, to design interventions accordingly.

***Keywords:*** *Artificial intelligence, AI competence, teacher competence, higher education, scale development.*

## Introduction

Artificial Intelligence (AI) is rapidly transforming the global landscape across all sectors, including health, management, finance, agriculture, and more (Zhai et al., 2021; Igami, 2020; Reddy et al., 2019). However, the education sector is the most affected by AI's rise. These developments are being integrated into teaching and learning processes, from intelligent tutoring systems and predictive analytics to AI-powered content creation software and adaptive learning environments. In the era of AI, educators must develop the skills necessary to understand, learn, and apply AI technologies in their pedagogical practices (UNESCO, 2024; Ng, 2021; Zhai et.al, 2021). Education systems are experiencing significant changes due to increasing AI use, but many substantial gaps remain in the effective implementation of AI in teaching to improve learning. These gaps are wider where digital transformation is not fully realised, and AI adoption lags further behind. AI is not just about acquiring skills; it also involves learning how to use it ethically, integrating it into teaching, and fostering critical thinking. Considering all these factors, a multifaceted understanding of AI competence is essential, encompassing knowledge, skills, attitude, and ethics (Ning et al., 2025).

There are several frameworks and tools created to evaluate the digital literacy and general ICT skills for integration into education (Tondeur et.al., 2017). In contrast, few instruments are crafted to measure the AI competence of teachers (Ning, 2025). A major proportion of developed tools is developed by high-income generating countries with sound digital and technological knowledge, which limits the scope of these instruments considering contextual realities, technological infrastructure, and pedagogical requirements of teachers in diverse global settings (Ning et.al., 2025; Koch et.al., 2024; Zhai et.al., 2021)

Since teachers act as a mediator between learning and technology, there is a pressing need to construct a context-sensitive, psychometrically sound instrument that can measure educators' preparedness and ability to function well with AI in teaching and learning processes. A validated scale would serve not only as a diagnostic tool in understanding professional development needs but also help inform policy-making, curriculum reform, and strategic investment in AI-related capacity development. AI promises to enhance personalization, ultimately increase the learners' engagement, and facilitate evidence-based decision-making (Holmes et al., 2019). Yet, the effective incorporation of AI in educational settings ultimately depends heavily on teachers' competence, including, technical competence, pedagogical adjustment and ethical discernment.

AI competence in a broader perspective is the ability of an individual to understand, assess, apply, and critically interact with AI technologies with the required knowledge, skills, attitude, and values (UNESCO, 2024). The required competence for an educator goes beyond user-level skills to the application of effective AI tools for teaching, the incorporation of AI into curriculum and courses, comprehending algorithms, and guiding students for ethical use of AI in learning (Holmes et.al., 2021).

The existing AI-related assessment scales significantly contribute to evaluating the AI awareness, attitudes, and competencies in the educational context. The developed instruments provide preliminary insights regarding the teachers' and students' perceptions and interaction with AI technologies. However, these AI assessment tools have gaps in conceptual exposure, contextual coverage, and digital/technological literacy in the AI era.

Most of these instruments are focused on an isolated dimension of AI competence, and some solely focus on AI literacy. Wang (2023) developed the Artificial Intelligence Literacy Scale (AILS) on its AIL framework, which has four domains, including AI awareness, AI usage, AI evaluation, and AI ethics. This scale was focused on AI literacy only, but not on teaching and learning. Similarly, the Artificial Intelligence Attitude Scale (AIAS) presented by Perkins et.al. (2024) consisted of three main factors, including trust in AI, concerns about AI, and perceived usefulness of AI. Artificial intelligence literacy Questionnaire (AILQ)

Ng et al. (2023) apply notion of AI literacy to educational context, presenting the concept of the ABCE model of learning Affective, Behavioral, Cognitive, and Ethical learning. This architecture has been tried out in secondary schools as well as universities, bringing a wider scope of the learners' views and actions. Although AILQ takes significant steps towards a multidimensional assessment of outcomes of AI-supported learning, it is still student-centered and fails to assess professional practices such as reflective teaching or continuous professional development.

The AI Competency Objective Scale (AICOS) developed by Markus et.al. (2025, preprint) is one of the most technically sound scales. AICOS uses an intensive Item-response theory (IRT) and addresses the major dimensions of objective AI literacy, which include knowledge, application, detection, creation, and ethics. It has been empirically validated on a German-speaking adult sample (N = 514) and shows high psychometric properties. Nevertheless, AICOS is an effective tool for assessing general AI competence, but not for educators or teaching environments.

Similarly, the Scale for Assessment of Non-Experts AI Literacy (SNAIL) designed by Laupichler et al. in 2023, is a psychometrically validated instrument used to assess the literacy of artificial intelligence in non-expert groups. The 31-item instrument has three fundamental factors, including technical comprehension, critical appraisal, and practical application. It has been confirmed both with the Western and non-Western population and in numerous cases, a large sample group of Turkish university students (Koch et.al., 2024). Although the SNAIL scale has been used to demonstrate good levels of comprehension of AI by laypersons, but lacks dimensions that apply to the pedagogical or professional teaching contexts.

The Meta AI Literacy Scale (MAILS) presented by Carolus et al. (2023) contains psychological and metacognitive terms, including AI self-efficacy, self-management, and ethics. It offers long and short versions validated with confirmatory factor analysis (CFA), and it supports its convergent validity with technological openness. MAILS, compared to pedagogical needs among educational professionals, is theoretically rich and statistically valid, but rather general and connected to the study population of adults in general (Koch et.al., 2024).

Considered collectively, these instruments provide valuable insights regarding general AI literacy, as well as the learning outcomes of students. Nevertheless, they lack a thorough, psychometrically verified instrument to measure AI competence, especially in teachers. The striking aspect is that the current available tools focus mainly on the general/student population and not on the educators or teachers; Ignore the pedagogical aspects of inquiry (e.g., instructional design, classroom applications), overlook the attitudinal and professional competencies that are critical towards the implementation of AI in an educational setting (e.g., collaboration, reflective practice, continuous development).

Based on these gaps, the study presented the need to develop the Artificial Intelligence Competence Teachers Assessment Scale (AICTAS). This tool conceptualizes competence in AI use in teaching as a three-dimensional construct including Cognitive competence, Attitudinal competence and Professional competence. The AICTAS explicitly includes the pedagogical, psychological, and professional dimensions of AI competence, thus incorporating a significant methodological gap in the research and practice. It also equips education institutions with a proper format on how to evaluate, educate and mentor teachers to incorporate AI in their teaching, thus helping in the preparation of teachers in education in the AI era.

## Methodology

The quantitative cross-sectional design of the study aimed to formulate and determine the validity of a new instrument, known as the Artificial Intelligence Competence Teachers Assessment Scale (AICTAS), to measure the multidimensional competence of AI among higher education teachers. The methodological framework adopted was the established scale development procedures (DeVellis, 2016) and included five stages named as the conceptualization of constructs and development of Items, content validation of Items by experts, pilot testing, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

The design of AICTAS was grounded on an extensive literature review on AI literacy (Ng et al., 2023; Laupichler et al., 2023), digital competence frameworks such as DigCompEdu designed by Redecker (2017), UNESCO AI competency framework for teachers (2024), and empirical research pointing to the importance of incorporating AI into the education sector. Based on this synthesis, teacher AI competence was theorized as a three-dimensional construct including cognitive competence, which covers (AI literacy, technological proficiency and AI integrated pedagogical skills), Attitudinal Competence (openness to innovation, adaptability, collaboration and communication) and Professional Competence (reflective practice, ethics and involvement in continuous professional development (CPD). The initial pool of scale consisted of 84 Items, which captured these three dimensions and their tributaries. All the Items were provided in the format of a declarative statement that had a 5-point Likert scale extending from 1 (Strongly Agree) to 5 (Strongly Disagree). An effort was made to include such positively worded, clearly articulated, and culture-neutral Items.

The content validity of the scale was confirmed after reviewing the initial draft by nine experts specialising in educational technology, AI in education, psychometrics, and teacher training. Each item was assessed on a four-point Likert scale to evaluate relevance, clarity, and representativeness concerning the target construct. The findings were based on their feedback, and following Lynn (1986), items with an Item-level Content Validity Index (I-CVI) below 0.78 were revised or removed.

The revised version of AICTAS was administered to collect 390 public and private sector university teachers. A stratified random sampling technique was adopted to ensure representation from different academic disciplines, including humanities and social sciences, natural sciences, information and technology, and commerce. An online mode of data collection was adopted to ensure accessibility while following all ethical protocols of research.

The underlying factor structure of AICTAS was assessed employing exploratory factor analysis (EFA) using the Principal Axis Factoring and Promax rotation, since it was assumed that there would be underlying factors which were correlated to each other. Before conducting EFA, Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett Test of Sphericity were employed to determine whether the data is appropriate to perform a factor analysis. Factorability was determined as a KMO greater than or equal to 0.80 and Bartlett test was marginally significant ($p < .001$) (Field, 2018). The Items were retained with factor loading ≥ 0.40 on their primary factor and minimal cross-loadings (less than 0.30 on secondary factors). The number of factors was identified by Eigenvalues >1, scree graph plot, and parallel analysis to determine the optimal count of components. The purpose of this analysis was to confirm that, proposed dimensions, including cognitive, attitudinal, and professional, distinctly emerged from the data.

To assess the internal consistency of the final instrument, its subscales, and the factor as a whole, Cronbach's alpha coefficients (α) were calculated. The George and Mallery (2003) scale of standards was used to assess the reliability levels; values >0.90 were considered outstanding, 0.80-0.89 as good, and 0.70-0.79 as acceptable.

The CFA was followed with EFA, Following the EFA, a CFA was conducted to validate the factor structure of the AICTAS scale. CFA verify the theoretical framework based on EFA (Joreskog, 1969), along with determining the degree to which the observed data fit the proposed three-dimensional construct that includes the aspects of cognitive, attitudinal, and professional competence.

The methodological framework approach ensures theoretical integrity and statistical robustness of AICTAS as a multidimensional instrument.

## Results

The following section presents detailed findings of every phase:

### Validation

Table 1 displays the I-CVI scores against the evaluation classification of each construct. It is clear from the scores that out of 84 items, most were deemed appropriate and scored above 0.79, with 57 items meeting relevance criteria, 59 under clarity criteria, and 60 under representativeness criteria. A notable number of items required revision, specifically 19 under relevance, 17 under clarity, and 16 under representativeness. Eight items were eliminated because of repetition, ambiguity, or non-relevance, while four items were included. The S-CVI of the scale was 0.84, which is considered acceptable (Polit & Beck, 2006).

*Table 1: Content Validity*

| Constructs | Appropriate (> 0.79) | | | Need Review (0.70 – 0.79) | | | Exclude (< 0.70) | | | Total Items |
|---|---|---|---|---|---|---|---|---|---|---|
| | Rele | Clar | Repr | Rele | Clar | Repr | Rele | Clar | Repr | |
| AI Literacy | 12 | 12 | 13 | 6 | 6 | 5 | 5 | 5 | 5 | 23 |
| Technological Proficiency | 4 | 8 | 11 | 7 | 3 | 0 | 2 | 2 | 2 | 13 |
| Pedagogical Skills | 13 | 13 | 13 | 3 | 3 | 3 | 1 | 1 | 1 | 17 |
| Attitudinal Competencies | 13 | 10 | 10 | 1 | 4 | 4 | 0 | 0 | 0 | 14 |
| Professional Competencies | 15 | 16 | 13 | 2 | 1 | 4 | 0 | 0 | 0 | 17 |
| Total | 57 | 59 | 60 | 19 | 17 | 16 | 8 | 8 | 8 | 84 |

*Rele= relevance, Clar=Clarity, Repr=Representativeness*

**Exploratory Factor Analysis (EFA)**

Both the KMO and Barlett's Test of Sphericity were used. The KMO index has a range of 0 to 1, and a value of 0.50 is generally accepted for factor analysis (Kaier, 1974). On the other hand, the Barlett's test of sphericity should be significant (p <.05), indicating a strong correlation between the items (Hair et al., 2014; Tabachnick & Fidell, 2014). Barlett's test of sphericity for 75 items was significant (p<.001), and the estimated value for the AICTA scale estimated KMO value is 0.808, confirming the suitability for factor analysis (Table 2).

***Table 2: KMO and Barlett's Test***

| | | |
|---|---|---|
| KMO Measure of Sampling Adequacy | | 0.808 |
| Barlett's Test of Sphericity | $\chi^2$ | 16,747.147 |
| | Df | 2211 |
| | *p*(Sig.) | < .001 |

It is evident from the principal component analysis (PCA), 13 components meet Kaiser's criterion for factor retention with eigenvalues greater than 1 (Kaiser, 1974). Table 3 shows that eigenvalues ranged from 1.552 to 7.201 for 13 components, and each explained total variance between 2.32% and 10.75%. The cumulative variance for these components accounted for 69.54% which is considered substantial in social science research (Hair et.al., 2014).

***Table 3: Total Variance Explained for AICTAS***

| Component | Initial Eigenvalues | | | Sums of Squared Loadings (Extracted) | | | Sums of Squared Loadings (Rotated) |
|---|---|---|---|---|---|---|---|
| | **Total** | **% of Variance** | **Cumulative %** | **Total** | **% of Variance** | **Cumulative %** | **Total** |
| 1 | 7.201 | 10.747 | 10.747 | 7.201 | 10.747 | 10.747 | 5.470 |
| 2 | 5.713 | 8.526 | 19.273 | 5.713 | 8.526 | 19.273 | 4.740 |
| 3 | 4.882 | 7.287 | 26.560 | 4.882 | 7.287 | 26.560 | 4.279 |
| 4 | 4.450 | 6.642 | 33.202 | 4.450 | 6.642 | 33.202 | 4.178 |
| 5 | 3.672 | 5.481 | 38.683 | 3.672 | 5.481 | 38.683 | 3.978 |
| 6 | 3.333 | 4.975 | 43.658 | 3.333 | 4.975 | 43.658 | 3.585 |
| 7 | 3.077 | 4.592 | 48.251 | 3.077 | 4.592 | 48.251 | 3.100 |
| 8 | 2.962 | 4.421 | 52.672 | 2.962 | 4.421 | 52.672 | 3.090 |
| 9 | 2.766 | 4.128 | 56.799 | 2.766 | 4.128 | 56.799 | 2.956 |
| 10 | 2.715 | 4.052 | 60.851 | 2.715 | 4.052 | 60.851 | 2.917 |
| 11 | 2.293 | 3.423 | 64.274 | 2.293 | 3.423 | 64.274 | 2.831 |
| 12 | 1.976 | 2.949 | 67.223 | 1.976 | 2.949 | 67.223 | 2.788 |
| 13 | 1.552 | 2.317 | 69.540 | 1.552 | 2.317 | 69.540 | 2.680 |

The PCA with Varimax rotation was conducted to present the rotated component matrix for factor loading of the initial 75 Items on 14 extracted components. The factor loading is considered acceptable and meaningful if 0.40 or above (Hair et.al., 2014). Most of the Items loaded strongly in a dominant factor, which depicts the clear and interpretable factor structure. Out of 75 Items, 8 Items were flagged for removal due to one or more reasons, including low factor loading, significant cross-loadings, and conceptual redundancy. The final retained 67 Items explained 69.61% of the total variance, indicative of a strong outcome for the multidimensional educational scale.

***Table 4: PCA with Varimax Rotation***

| | Components | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
| St38 | .793 | | | | | | | | | | .338 | | | |
| St35 | .745 | | | | | | | | | | .433 | | | |
| St74 | .744 | | | .420 | | | | | | | | | | |
| St20 | .707 | | | | | | .474 | | | | | | | |
| St29 | .694 | | | | | | | .575 | | | | | | |
| St19 | .669 | | | | | | .542 | | | | | | | |
| St18 | .663 | | | | | | .562 | | | | | | | |
| St64 | | .853 | | | | | | | | | | | | |
| St62 | | .850 | | | | | | | | | | | | |
| St63 | | .839 | | | | | | | | | | | | |
| St66 | | .823 | | | | | | | | | | | | |
| St67 | | .822 | | | | | | | | | | | | |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| St60 | | .807 | | | | | | | | | | | | |
| St61 | | .800 | | | | | | | | | | | | |
| St65 | | .751 | | | | | | | | | | | | |
| St59 | .534 | .589 | | | | | | | | | | | | |
| St57 | | | .784 | | | | | | | | | | | |
| St52 | .417 | | .771 | | | | | | | | | | | |
| St55 | .412 | | .750 | | | | | | | | | | | |
| St53 | .437 | | .749 | | | | | | | | | | | |
| St54 | | | .743 | | | | | | | | | | | |
| St58 | | | .743 | | | | | | | | | | | |
| St56 | .524 | | .707 | | | | | | | | | | | |
| St50 | -.309 | | .699 | | | | | | | | | | | |
| St51 | .553 | | .690 | | | | | | | | | | | |
| St68 | | | | .835 | | | | | | | | | | |
| St75 | | | | .823 | | | | | | | | | | |
| St70 | | | | .820 | | | | | | | | | | |
| St72 | | | | .803 | | | | | | | | | | |
| St73 | | | | .780 | | | | | | | | | | |
| St69 | | | | .779 | | | | | | | | | | |
| St71 | | | | .739 | | | | | | | | | | |
| St4 | | | | | .777 | | | | | | | | | |
| St2 | | | | | .761 | | | | | | | | | |
| St1 | | | | | .745 | | | | | | | | | |
| St7 | | | | | .742 | | | | | | | | | .302 |
| St6 | | | | | .732 | | | | | | | | | |
| St3 | | | | | .724 | | | | | | | | | |
| St5 | | | | | .723 | | | | | | | | | |
| St10 | | | | | | .874 | | | | | | | | |
| St8 | | | | | | .868 | | | | | | | | |
| St11 | | | | | | .863 | | | | | | | | |
| St9 | | | | | | .844 | | | | | | | | |
| St21 | | | | | | | .842 | | | | | | | |
| St23 | | | | | | | .839 | | | | | | | |
| St22 | | | | | | | .795 | | | | | | | |
| St24 | .415 | | | | | | .706 | | | | | | | |
| St31 | | | | | | | | .818 | | | | | | |
| St33 | | | | | | | | .799 | | | | | | |
| St30 | | | | | | | | .747 | | | | | | |
| St34 | | | | | | | | .742 | | | | | | |
| St32 | | | | | | | | .686 | | | | | | |
| St48 | | | | | | | | | .814 | | | | | |
| St46 | | | | | | | | | .800 | | | | | |
| St49 | | | | | | | | | .797 | | | | | |
| St45 | | | | | | | | | .744 | | | | | |
| St47 | | | | | | | | | .694 | | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| St15 | | | .836 | | | | |
| St17 | | | .829 | | | | |
| St16 | | | .754 | | | | |
| St14 | | | .687 | | | | |
| St13 | .519 | | .538 | | | | .386 |
| St39 | | | | .824 | | | |
| St40 | | | | .821 | | | |
| St37 | | | | .804 | | | |
| St36 | .337 | | | .689 | | | |
| St41 | | | | | .857 | | |
| St42 | | | | | .820 | | |
| St43 | | | | | .817 | | |
| St44 | | | | | .795 | | |
| St26 | | | | | | .829 | |
| St27 | | | | | | .829 | |
| St28 | | | | | | .779 | |
| St25 | .303 | | | | | .752 | |
| St12 | -.407 | .500 | | | | | .507 |

## Reliability

The Cronbach's Alpha if Item deleted values depict how removing each Item can affect the reliability of the scale. The analysis shows that the scale is consistent and stable, with overall high reliability (α = .832), whereas no items showed significantly higher alpha.

***Table 5: Descriptive Statistics and Cronbach's Alpha***

| Items | Mean | Std. Deviation | α if Item Deleted |
|---|---|---|---|
| St1 | 3.35 | 1.040 | .831 |
| St2 | 3.48 | 1.003 | .830 |
| St3 | 3.42 | .950 | .830 |
| St4 | 3.57 | .998 | .830 |
| St5 | 3.92 | 1.028 | .835 |
| St6 | 3.57 | .950 | .829 |
| St7 | 4.13 | .923 | .832 |
| St8 | 3.66 | .970 | .829 |
| St9 | 3.97 | .954 | .828 |
| St10 | 3.66 | .959 | .831 |
| St11 | 3.76 | .943 | .831 |
| St12 | 3.48 | .982 | .832 |
| St13 | 3.57 | .926 | .830 |
| St14 | 3.98 | .929 | .828 |
| St15 | 3.58 | .908 | .831 |

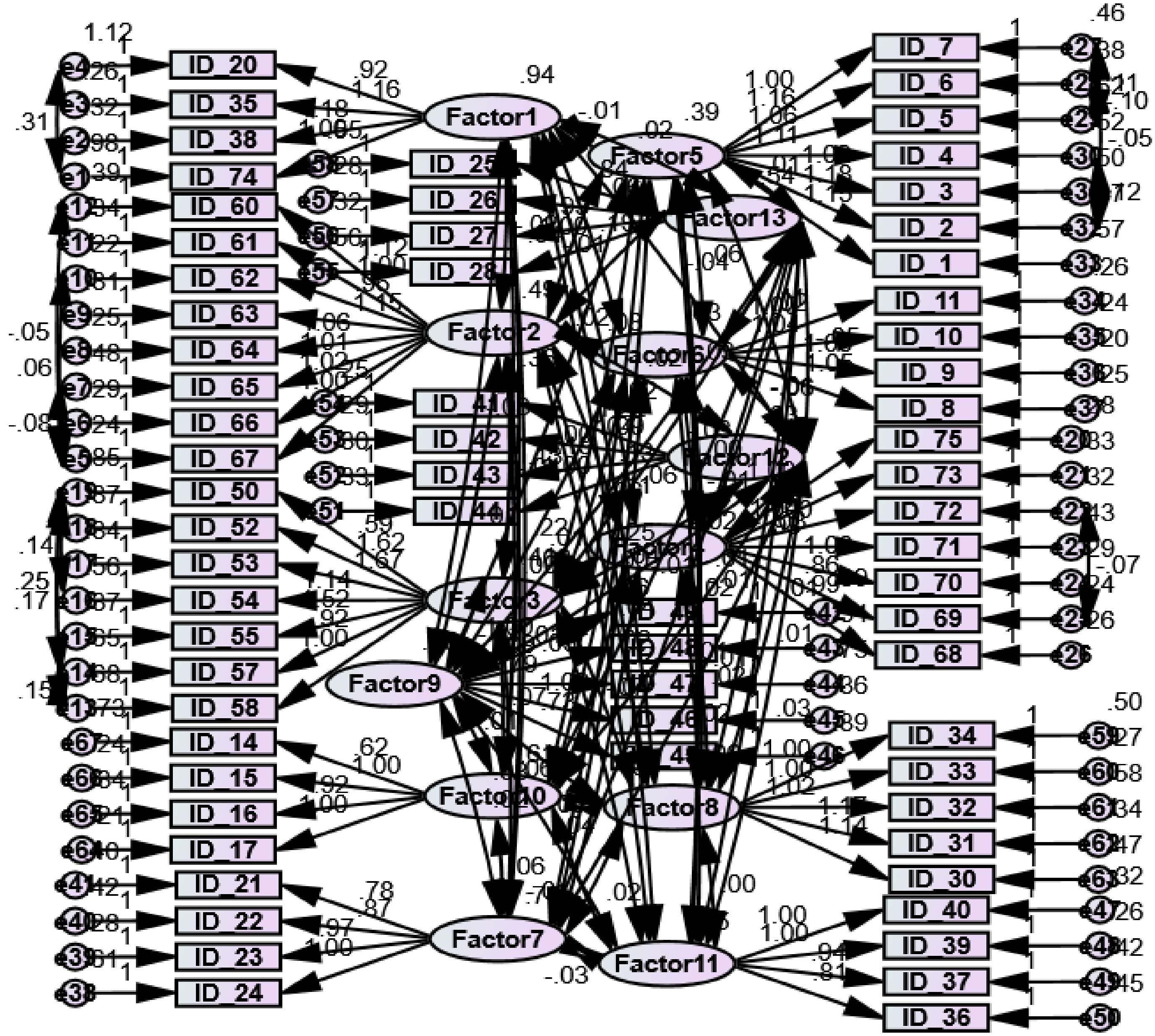
| | | | |
|---|---|---|---|
| St16 | 3.55 | 1.385 | .825 |
| St17 | 3.72 | .913 | .833 |
| St18 | 3.80 | .971 | .831 |
| St19 | 4.01 | .965 | .831 |
| St20 | 3.86 | 1.146 | .828 |
| St21 | 3.99 | .969 | .830 |
| St22 | 3.67 | .949 | .834 |
| St23 | 3.79 | .890 | .832 |
| St24 | 3.62 | 1.054 | .835 |
| St25 | 3.66 | .970 | .831 |
| St26 | 3.78 | .919 | .831 |
| St27 | 3.67 | .980 | .831 |
| St28 | 3.97 | .798 | .831 |
| St29 | 3.75 | .931 | .832 |
| St30 | 2.93 | 1.232 | .825 |
| St31 | 4.08 | .865 | .830 |
| St32 | 3.89 | .905 | .832 |
| St33 | 3.21 | 1.273 | .825 |
| St34 | 3.75 | .844 | .833 |
| St35 | 3.68 | .878 | .834 |
| St36 | 3.97 | .864 | .832 |
| St37 | 3.86 | .826 | .832 |
| St38 | 3.61 | .883 | .834 |
| St39 | 3.86 | .817 | .834 |
| St40 | 4.04 | .809 | .831 |
| St41 | 3.43 | .980 | .834 |
| St42 | 3.54 | 1.033 | .830 |
| St43 | 3.51 | .975 | .834 |
| St44 | 3.46 | .950 | .833 |
| St45 | 3.55 | 1.002 | .832 |
| St46 | 3.04 | 1.208 | .826 |
| St47 | 3.15 | 1.218 | .826 |
| St48 | 3.47 | 1.048 | .828 |
| St49 | 3.02 | 1.152 | .827 |
| St50 | 3.37 | .998 | .830 |
| St51 | 3.59 | 1.047 | .830 |
| St52 | 3.53 | 1.003 | .831 |

| | | | |
|---|---|---|---|
| St53 | 3.85 | .911 | .828 |
| St54 | 4.00 | .821 | .830 |
| St55 | 3.51 | .982 | .831 |
| St56 | 3.95 | .894 | .830 |
| St57 | 3.85 | .990 | .827 |
| St58 | 3.78 | .895 | .831 |
| St59 | 3.87 | .858 | .830 |
| St60 | 3.81 | .852 | .831 |
| St61 | 4.09 | .768 | .828 |
| St62 | 3.67 | .872 | .831 |
| St63 | 3.93 | .916 | .828 |
| St64 | 3.55 | .910 | .831 |
| St65 | 3.89 | .852 | .830 |
| St66 | 3.53 | 1.386 | .823 |
| St67 | 3.82 | .869 | .831 |

**Confirmatory Factor Analysis (CFA)**

The Maximum Likelihood Estimation (MLE) method was applied in calculating the estimations. The model consisted of 67 Items that were retained and subdivided into 13 sub-factors based on the latent constructs identified during the EFA. Covariances among the residuals were then permitted wherever modification indexes and theoretical reasoning allowed them to be accepted.

**Figure 1: MLE Model after Covariance**




Initially, the employed model showed adequate fit, though a few indices were marginal. Once the specified error terms were correlated, the model got a better fit ($\chi^2/df$ = 2.39; CFI = 0.818; RMSEA = 0.060), indicating empirically valid items and theoretically sound structure.

*Table 6: Model Fit after Covariance*

| Fit Index | Value |
|---|---|
| $\chi^2/df$ | 2.385 |
| GFI | .707 |
| AGFI | .675 |
| CFI | .818 |
| RMSEA | .060 |

The factor loadings ranged between 0.50 to 0.85, and all standardized regression weights were also found significant (p < .001), which showed that the Items had a strong congruence with their corresponding latent constructs. These findings corroborate the validity of the AICTAS instrument in a multidimensional nature while confirming the appropriateness of the scale in education research and teacher evaluation. The validated version of AICTAS overall Cronbach's Alpha was 0.840, which confirmed the scale's reliability.

***Table 7: Reliability Statistics by Factors***

| Domains | Factors | No. of Items | Serial No. in Scale | Cronbach's Alpha |
|---|---|---|---|---|
| **Cognitive Competence** | | | | |
| Ai literacy | Awareness of AI | 7 | 1 - 7 | 0.847 |
| | AI in Research | 4 | 8 - 11 | 0.802 |
| | Ethical AI use | 4 | 12 - 15 | 0.819 |
| Technological proficiency | Foundational technological skills | 4 | 16 - 19 | 0.817 |
| | Innovation,and Institutional Support | 4 | 20 – 23 | 0.823 |
| Pedagogical skills | Planning for Lessons | 5 | 24 – 28 | 0.840 |
| | Managing students | 4 | 29 – 32 | 0.851 |
| | Assessing learning | 4 | 33 – 36 | 0.808 |
| | Support and Mentorship | 4 | 37 – 40 | 0.884 |
| **Attitudinal Competence** | | | | |
| | Collaboration,and Communication | 5 | 41 – 45 | 0.874 |
| | Openness,and Adaptability | 7 | 46 – 52 | 0.890 |
| **Professional Competence** | | | | |
| | Reflective practices | 8 | 53 - 60 | 0.815 |
| | Continuous professional development | 7 | 61 - 67 | 0.860 |

## Conclusion

The Artificial Intelligence Competence Teachers' Assessment Scale (AICTAS) was developed after an extensive literature review on AI literacy, digital competence frameworks, AI competency frameworks and empirical research pointing to the importance of incorporating AI into the education sector. Based on this synthesis, teacher AI competence was theorized as a three-dimensional construct including cognitive competence, attitudinal competence, and professional competence. The final set of 67 Items demonstrated strong psychometric properties, sound validity, and high internal consistency across 13 factors. The rigorous analysis involving EFA and CFA confirmed the empirical structuring of the scale. The model fit indices confirmed that AICTAS is a statistically reliable instrument with strong theoretical ground to assess the multidimensional AI competence and readiness of higher education teachers. This scale not only fills the existing research gap but also enables educational leaders, policymakers, and professional developers to better understand the needs and competencies of teachers, which can help in identifying specific domains for targeted interventions to improve teaching with AI.

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