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Development and Validation of the Attitude Toward Artificial Intelligence in Mathematics Learning (AT-AIML) Scale

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ABSTRACT

This study developed and examined the psychometric properties of the Attitude Toward Artificial Intelligence in Mathematics Learning (AT-AIML) Scale designed to assess pre-service mathematics teachers' attitudes toward artificial intelligence integration in mathematics education. An initial 30-item instrument representing cognitive, affective, and behavioral dimensions was administered to 157 pre-service mathematics teachers during the first semester of School Year 2024–2025. Following preliminary screening, four items were removed to address a non-positive-definite correlation matrix. The remaining 26 items underwent exploratory dimensionality analysis using principal component analysis with Promax oblique rotation. The Kaiser–Meyer–Olkin measure of sampling adequacy was 0.655, while Bartlett's test of sphericity was statistically significant. Two components were retained, accounting for 84.16% of the total variance. The first factor, Attitude Toward the Role of AI in Learning Mathematics and Problem-Solving, comprised 20 items, while the second factor, Attitude Toward the Integration of AI in Mathematics Education, comprised six items. Internal consistency analysis yielded Cronbach's alpha coefficients of 0.989 and 0.939 for the respective factors and 0.987 for the overall scale. The reported composite rating of 3.37 indicated a somewhat favorable attitude toward artificial intelligence in mathematics learning. The findings provide preliminary evidence supporting the dimensional structure and internal consistency of the developed instrument. However, further validation using independent samples, confirmatory factor analysis, and additional reliability and validity measures is recommended. The AT-AIML Scale may serve as a preliminary research instrument for examining attitudes toward artificial intelligence among pre-service mathematics teachers and informing the development of appropriate technology integration initiatives in mathematics education.

Keywords: *Artificial Intelligence, Attitude Measurement, Mathematics Education, Pre-Service Mathematics Teachers, Scale Development, Exploratory Factor Analysis, Principal Component Analysis, Internal Consistency*

INTRODUCTION

Artificial Intelligence (AI) has been used to most of computer programs and systems to perform more complex tasks than common computer programs (McCarthy, 2007). Innovation in AI has improved and changed the way people live, work, and communicate with one another (Netexplo, 2019). AI features are now widely used in many areas, such as automation, information processing, national security, e-commerce, medical, entertainment, and most importantly, education.

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With the rapid development of AI technology in recent years, using AI in education has become increasingly observed in many schools. The emergence of these innovative technologies in teaching and learning methods is exceptionally beneficial and significant in the classroom (Shafie, 2019; Huang, 2021) as it allows teachers to access more updated information. This can improve their teaching as it is attractive, user-friendly, relevant, interactive and provide learning experiences more effectively (Huang, 2021). With these advantages, teachers can successfully integrate digital technologies into the teaching and learning process and technological opportunities (Bozkurt et al., 2021).

Moreover, personalized learning can provide meaningful learning experiences and intelligent learning tracking to assist learner enhance their learning ability and efficiency according to their needs and learning situations (Dishon, 2017). Hence, learning in the AI era should be student-centered, with students leading learning activities (Chang and Lu, 2019) and creating their own unique learning pathways (Chaudhri et al., 2013). It is designed to enable each student's academic performance by evaluating their learning needs, interests, and goals and then creating learning experiences that meet the needs of individuals or groups of learners (Southgate et al., 2019).

According to Gao (2020), artificial intelligence continues to develop and innovate based on the development of computer technology. It can enable learners to enhance their mathematical and cognitive skills in learning. Popenici and Kerr (2017) state that the role of technology in higher learning is to enhance human thinking and improve the educational process. AI helps students find answers easier and more efficiently. All information about the lesson can be easily accessed by students using this innovative intelligence. In this generation, students are more inclined to learn and explore new knowledge on their own, so this powerful AI tool can help students explore more without waiting for an educator. Cope et al. (2020) indicate, however, that the role of AI should never 'take over' the educator's duty in any way. Furthermore, deploying these technologies for teaching, learning, student assistance, and administration faces various hurdles (Popenici & Kerr, 2017).

Artificial Intelligence (AI) in the Philippine educational system has catapulted scholarly discourses on the line. Studies argue on academic concerns and challenges of AI in education (AIED), the initial footholds for data center hubs, potential offerings for enhanced learning experiences, data-driven decision-making, and foreseen opportunities. However, AIED requires a robust technological infrastructure and adequate computing resources aligned with policy frameworks, such as addressing data privacy concerns, the digital divide, and ongoing faculty training and development (Estrellado et al., 2023).

Moreover, artificial intelligence has become integral to various contemporary technologies, such as social media platforms, devices, and education. At the same time, research on the public acceptance of AI shows that many people, particularly students, feel quite apprehensive about the potential of such technologies. This observation has been connected to demographic and sociocultural user variables (e.g., attitude, motivation, etc.).

To develop appropriate statements for the scales to ascertain learners' attitude towards artificial intelligence in Mathematics learning, the dimensions of attitude and types of artificial intelligence are considered.

Specifically, the study sought to:

1. Construct scale items based on the cognitive, affective, and behavioral dimensions of pre-service teachers' attitudes toward AI in mathematics learning.
2. Examine the descriptive item characteristics of the initial instrument.
3. Establish the underlying factor structure of the scale through Exploratory Factor Analysis (EFA).
4. Evaluate the internal consistency reliability of the extracted factors and the composite instrument using Cronbach's alpha.

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METHODS

Research Design

The study employed a quantitative scale-development and preliminary psychometric validation approach, using descriptive statistics, principal component analysis with Promax rotation, and internal consistency analysis.

Scale Development Process

Based on the components of attitude and types of artificial intelligence, sets of items were constructed for the three dimensions of the scale. The first dimension (10 items) was a cognitive component of attitude on artificial narrow intelligence, the second dimension (10 items) was about the affective component of attitude on artificial narrow intelligence, and the third dimension (10 items) was about the behavior component of attitude on artificial narrow intelligence. Every item in the instrument used the 6-point Likert Scale consisting of six ratings ranging from 1(Very Unfavorable), 2(Unfavorable), 3(Somewhat Favorable), 4(Favorable), 5(Much Favorable), and 6(Very Much Favorable).

Sampling Procedure

The respondents of the study were the population of Mathematics major pre-service teachers enrolled in the College of Teacher Education in the first semester of S.Y. 2024-2025. A total of 157 students were the respondents in the study.

Item Scale Administration

The mathematics teachers were requested that their students will be involved in the study. Upon approval, the Google Form link was sent to the group chat of the students, and the mechanics and the purpose of the data being used for research and not disclosed to a non-member of the study were explained to them.

Data Analysis

The final draft of the instrument with 30 items was administered to the 157 respondents, and the dataset was retrieved from Google Drive, where the Google Form was constructed. The dataset was resaved in the Excel Workbook format for easier editing and saving. Upon securing the dataset, checking for errors was done to prepare for the analysis. The data acquired was analyzed using the IBM Statistical Package on Social Sciences (SPSS version 23).

Before the analyses, the ratings for the negative statements were decoded. Cronbach's alpha was used to test the reliability of the items. Moreover, factor analysis using the principal component method followed by Promax Rotation was applied to reveal the scale's structure. Until then, the original 30 items were trimmed down to 26 items. They were reassigned to two dimensions: factor 1 (Attitude towards the Role of AI in Learning Mathematics and Problem-Solving) and factor 2 (Attitude towards the Integration of AI in Mathematics Education). Furthermore, factor 1 has 20 items, while factor 2 has six.

Ethical Considerations

The confidentiality of data gathered ensures participants that personally identifiable information were not included in any disseminated reports or publications nor to be disclosed in a non-member of this study. The researcher also provided informed consent regarding the research objectives, possible benefits, how the findings used, any potential negative consequences of participation, and who have access to the findings. The researcher has the responsibility that the study caused no harm to the participants during the evaluation process (intentional or otherwise).

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Table 1. *Initial theoretical dimensions*

Dimension	Number of items
Cognitive	10
Affective	10
Behavioral	10
Total	30

Table 2. *Response scale*

Rating	Interpretation
6	Very Much Favorable
5	Much Favorable
4	Favorable
3	Somewhat Favorable
2	Unfavorable
1	Very Unfavorable

RESULTS

Descriptive Characteristics

Item means ranged from 2.79 to 4.36, and standard deviations ranged from 1.06 to 1.75. Most items had observed minimum and maximum ratings of 1 and 6, respectively.

Table 3. *Descriptive characteristics of the initial items*

Item	Mean	SD	Max	Min
1	3.78	1.34	6	1
2	3.88	1.34	6	2
3	3.62	1.34	6	1
4	3.20	1.32	6	1
5	3.32	1.22	6	1
6	3.52	1.22	6	1
7	3.75	1.53	6	1
8	3.10	1.39	6	1
9	3.06	1.06	5	1
10	3.25	1.45	6	1
11	3.48	1.49	6	1
12	3.09	1.26	5	1
13	2.79	1.09	5	1
14	3.01	1.28	6	1
15	3.09	1.32	6	1
16	3.38	1.62	6	1
17	3.81	1.67	6	1
18	4.36	1.75	6	1
19	4.28	1.70	6	1
20	4.28	1.50	6	1
21	3.92	1.53	6	1
22	3.84	1.42	6	1
23	3.54	1.46	6	1
24	3.43	1.43	6	1
25	3.10	1.54	6	1
26	2.92	1.27	5	1
27	3.65	1.64	6	1
28	3.19	1.34	6	1

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Item	Mean	SD	Max	Min
29	3.23	1.21	5	1
30	2.97	1.28	6	1

Initial Reliability Analysis

The initial 30-item scale obtained Cronbach's alpha of 0.951.

Table 4. *Initial reliability analysis*

Number of Items	Cronbach's Alpha	Interpretation
30	0.951	Excellent Reliability

Correlation Matrix Screening and Sampling Adequacy

The initial correlation matrix was not positive definite. Items 17, 18, 19, and 20 were removed. The KMO measure was 0.655 and Bartlett's test was significant, $\chi^2(325) = 6{,}650.475$, $p < .001$.

Table 5. *KMO and Bartlett's test*

Indicator	Result
KMO	0.655
Approximate chi-square	6650.475
Degrees of freedom	325
Significance	< .001

Dimensional Structure

Two components with eigenvalues greater than 1 were retained, accounting for 84.160% of total variance.

Table 6. *Initial eigenvalues and variance explained*

Component	Total	Percentage of Variance	Cumulative Percentage
1	19.827	76.258	76.258
2	2.054	7.902	84.160

Component Correlation

The two components had a positive correlation of 0.695 following Promax rotation.

Table 7. *Component correlation matrix*

Component	Component 1	Component 2
Component 1	1.000	0.695
Component 2	0.695	1.000

Scree Plot

The original scree plot showed a sharp decline across the first two components followed by a leveling of the remaining eigenvalues, supporting the two-component solution.

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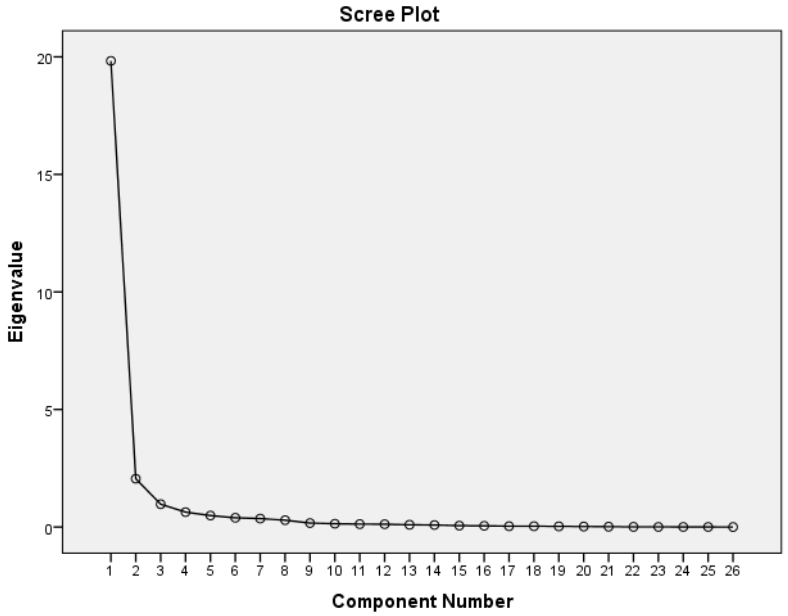


Figure 1. Scree plot showing the number of components to be retained

Factor Structures and Item Loadings

Factor 1: Attitude Toward the Role of AI in Learning Mathematics and Problem-Solving

Twenty items were assigned to Factor 1, with reported coefficients ranging from 0.521 to 1.142.

Table 8. *Statements for Factor 1 following Promax rotation*

Item	Statement	Coefficient
28	I answer my homework in Mathematics with the help of artificial intelligence.	1.142
10	I believe in the capability of AI to improve my performance in Mathematics.	0.991
24	I visualize Mathematics problems effectively using AI.	0.974
26	I provide several solutions to Mathematics problems using AI tools.	0.962
3	The use of artificial intelligence can improve my performance in Mathematics.	0.956
23	I assess and evaluate my Mathematics learning with AI.	0.951
16	I think artificial intelligence can be used as a learning material for mathematics.	0.933
11	I am comfortable using artificial intelligence to learn Mathematics.	0.922
1	Artificial intelligence can improve my Mathematics learning.	0.909
29	I keep on improving my abilities in Mathematics problem-solving using artificial intelligence.	0.874
2	Artificial intelligence can help me solve difficult problems in Mathematics.	0.870
25	I solve Mathematics problems more efficiently using AI.	0.844
27	I use AI to verify the accuracy of my answers to mathematics problems.	0.842
22	I identify errors in my solutions using artificial intelligence.	0.836
7	I believe that artificial intelligence can provide solutions to problems in mathematics.	0.818
21	I use artificial intelligence to assist in my learning of mathematics.	0.810
13	I feel that I can understand Mathematics better using AI.	0.746
30	I use AI to personalize my learning of Mathematics lessons.	0.661
14	Using artificial intelligence in mathematics can increase my motivation to learn.	0.555

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Item	Statement	Coefficient
15	Artificial intelligence can enhance interest in solving Mathematics problems.	0.521

Factor 2: Attitude Toward the Integration of AI in Mathematics Education

Six items were assigned to Factor 2, with reported coefficients ranging from 0.527 to 1.078.

Table 9. *Statements for Factor 2 following Promax rotation*

Item	Statement	Coefficient
5	Artificial intelligence can be incorporated into Mathematics instruction.	1.078
4	I believe that artificial intelligence can make Mathematics learning easier.	1.006
6	Artificial intelligence tools can aid in understanding Mathematics lessons.	0.924
9	The role of artificial intelligence is crucial in Mathematics education.	0.811
8	I can fully understand and solve all Mathematics problems using artificial intelligence.	0.534
12	The use of artificial intelligence can make Mathematics learning more enjoyable.	0.527

Final Reliability Analysis

The final scale obtained alpha of 0.987, with coefficients of 0.989 and 0.939 for Factors 1 and 2, respectively.

Table 10. *Final reliability analysis*

Factor	Number of Items	Cronbach's Alpha	Interpretation
Scale	26	0.987	Excellent Reliability
Factor 1	20	0.989	Excellent Reliability
Factor 2	6	0.939	Excellent Reliability

Summary of Scale Ratings

Table 11. *Reported scale ratings*

Factor	Eigenvalue	Average rating	Weighted score
1	19.827	3.39	67.214
2	2.054	3.21	6.593
Total	21.881	—	73.807
Scale rating	—	3.37	—

The reported composite rating was 3.37, interpreted in the source as somewhat favorable. The weighting procedure used the reported eigenvalues.

DISCUSSION

Dimensional Structure

The two retained components accounted for 84.16% of variance and correlated at 0.695. These findings provide preliminary evidence of related dimensions, consistent with the multidimensional perspectives discussed by Gouveia et al. (2001) and Osmani et al. (2024). Principal component analysis describes the organization of observed responses rather than independently confirming a latent factor model.

Role of AI in Learning and Problem-Solving

Moreover, the items emphasize artificial intelligence's ability to improve performance, promote learner motivation, and deliver appropriate solutions and feedback. These features show the practical use of AI and its potential to make Mathematics learning more engaging and efficient. The findings align with recent research indicating that AI integration in education supports adaptive learning and learner-centered

approaches (Holmes et al., 2019; Zawacki-Richter et al., 2019), making it a pivotal tool in modern pedagogy.

The statements measure perceived benefits and reported practices, not independently measured improvements in mathematical performance.

Integration of AI in Mathematics Education

Moreover, the findings suggest that AI can be an effective pedagogical tool by facilitating adaptive learning, providing personalized feedback, and supporting diverse learning needs (Chen et al., 2020; Li et al., 2022). This aligns with recent studies that argue AI integration in education can enhance the learning experience by offering tailored instructional methods and fostering greater student engagement (Holmes et al., 2019).

Favorable attitudes do not independently establish instructional competence or effectiveness.

Internal Consistency

The high alpha coefficients support internal consistency within the sample (DeVellis, 2017; Taber, 2018). However, exceptionally high coefficients may indicate item redundancy. Coefficients above 1.00 may occur in oblique pattern matrices; the original rotated output should be examined before interpreting them.

Attitudes and Educational Implications

The reported rating of 3.37 was interpreted as somewhat favorable. Factor 1 had a higher descriptive rating than Factor 2, but no inferential comparison was reported. Teacher education programs may consider responsible AI integration, verification of generated solutions, and independent mathematical reasoning.

Limitations

The sample consisted of 157 pre-service mathematics teachers. Generalizability to other populations remains untested. Confirmatory factor analysis, test–retest reliability, convergent and discriminant validity, and criterion-related validity were not reported. The complete correlation matrix, item-removal diagnostics, communalities, and rotated pattern and structure matrices were unavailable. The eigenvalue-weighted scoring procedure requires further justification. The results measure attitudes and reported practices, not causal effects on learning outcomes.

CONCLUSION

The AT-AIML Scale was reduced from 30 to 26 items following correlation matrix screening. Two related components accounted for 84.16% of variance. The overall alpha of 0.987 and factor coefficients of 0.989 and 0.939 provide preliminary evidence of internal consistency. The reported composite rating of 3.37 indicated a somewhat favorable attitude. Further independent validation is necessary before standardized use.

Recommendations

1. Mathematics teachers could consider integrating artificial intelligence tools into the curriculum to capitalize on their potential for enhancing problem-solving skills, enhancing student motivation, and providing personalized learning experiences.
2. Training programs could be designed to assist Mathematics teachers to effectively integrate AI tools into their teaching practices.
3. Educational stakeholders could develop guidelines and policies to support the ethical and effective integration of AI in mathematics education.
4. Future researchers could investigate specific AI tools and applications that align with the two identified factors to determine their impact on learning outcomes and attitudes in mathematics education.

5. Longitudinal studies could be conducted to assess the long-term effects of AI integration on students' attitudes and performance in Mathematics education.
6. The validated scale could be adapted to be used in other subject areas to assess attitudes toward AI across different educational disciplines.

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