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Development and Validation of Attitudes and Behavioural Measurement Scales on Artificial Intelligence Integration in Mathematics Teaching among Pre-Service Teachers in Abuja, Nigeria

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Abstract

The increasing use of artificial intelligence (AI) in education has created a need for concise, context-specific measures of teachers' orientations toward AI use. However, existing instruments often combine attitude, behavioural intention, perceived usefulness, self-efficacy, anxiety, and other acceptance-related constructs. This study developed and evaluated a concise measure of Attitude Toward Use (ATT) and Behavioural Intention to Use (BIU) artificial intelligence in mathematics teaching and learning among pre-service mathematics teachers. A quantitative cross-sectional survey was conducted with 221 pre-service mathematics teachers from higher institutions in the Federal Capital Territory, Abuja, Nigeria. Items were generated from the Technology Acceptance Model and relevant literature, subjected to expert evaluation, and examined using separate one-factor measurement models. Model fit was assessed using x^2, CFI, TLI, RMSEA, and SRMR, while reliability was evaluated using McDonald's coefficient omega. The initial ATT model demonstrated inadequate fit, but substantial improvement was obtained following item refinement (CFI = .990, TLI = .938, SRMR = .019, RMSEA = .120). The retained ATT indicators loaded from .528 to .818, with ω = .715. The BIU model demonstrated stronger fit ($x^2(5)$ = 11.455, CFI = .986, TLI = .972, RMSEA = .076, SRMR = .025), with factor loadings ranging from .588 to .773 and ω = .786. The findings provide preliminary evidence for concise, construct-specific measures of ATT and BIU toward AI use in mathematics teaching and learning. The BIU scale demonstrated stronger measurement performance, whereas the ATT scale requires further validation using independent samples.

Keywords: Artificial intelligence; behavioural Intention; attitude; mathematics, pre-service teachers

Introduction

The educational significance of artificial intelligence (AI) increasingly depends not only on its technical capabilities but also on whether teachers are willing to incorporate it into meaningful instructional practice. This issue is particularly consequential in mathematics education, where AI can support lesson preparation, instructional resource development, mathematical explanation, problem solving, assessment, and feedback. The emergence of generative artificial intelligence (GenAI) has expanded these possibilities while raising questions about how prospective teachers evaluate AI use and whether they intend to incorporate it into their future professional practice (Deshen et al., 2026). For pre-service mathematics teachers, who are preparing to teach in increasingly technology-mediated environments, understanding these orientations is therefore both an educational and measurement concern. Importantly, the availability of AI does not by itself establish meaningful educational integration; such integration also depends on educators' evaluations of its use and their intentions to employ it. UNESCO (2023) accordingly emphasises human agency, pedagogical appropriateness, equity, safety, and responsible use in the integration of GenAI into education.

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Teacher education provides an important context for examining these issues because pre-service teachers are developing professional orientations that may inform their subsequent classroom practices. Research has increasingly examined prospective teachers' attitudes toward AI and their intentions to use it, but these constructs have been operationalised differently across studies (Bui et al., 2025; Zhang et al., 2023). This variation raises a fundamental measurement question: when the objective is to determine whether future teachers are favourably disposed toward AI use and whether they intend to employ it, what precisely should constitute the indicators of these constructs? The question is especially relevant in mathematics education because AI use involves mathematical and pedagogical judgement. Although AI can assist with generating examples, exploring solution strategies, preparing learning activities, and developing instructional resources, teachers remain responsible for evaluating the mathematical accuracy and pedagogical appropriateness of AI-generated outputs (Cevikbas & Kaiser, 2026). Thus, a general favourable orientation toward AI does not necessarily represent a favourable evaluation of its use in mathematics education, just as an intention to use AI for general academic purposes does not necessarily imply an intention to integrate it into mathematics teaching. The behavioural referent of measurement must therefore be specified to distinguish general technological acceptance from acceptance of AI use within a particular professional domain (Stein et al., 2024).

The Technology Acceptance Model (TAM) provides an established theoretical foundation for explaining technology acceptance. Davis (1989) developed and validated measures of perceived usefulness and perceived ease of use and proposed these beliefs as fundamental determinants of user acceptance of information technology. Davis et al. (1989) subsequently compared TAM with the Theory of Reasoned Action and examined relationships among attitudes, subjective norms, perceived usefulness, perceived ease of use, behavioural intentions, and computer use. Their findings showed that behavioural intention was related to subsequent system use, while perceived usefulness exerted a substantial influence on intention. Perceived ease of use also contributed to intention, although its effect diminished over time. The authors further found that attitude did not add substantially to the prediction of intention once the effects of the other TAM variables were considered. The present study does not seek to reproduce or test this predictive structure. Rather, it focuses on developing concise measures of respondents' evaluations of AI use and their intentions to use AI in mathematics education. Perceived usefulness and perceived ease of use are consequently treated as theoretically relevant antecedent beliefs rather than indicators of behavioural intention.

The measurement of attitudes toward AI has expanded considerably, but existing instruments differ in construct definition and dimensionality. Suh and Ahn (2022), for example, developed the Scale of Attitude Toward Artificial Intelligence (SATAI) and conceptualised AI attitudes across cognitive, affective, and behavioural dimensions. Grassini (2023) subsequently demonstrated the feasibility of a brief four-item AI attitude measure, while also illustrating the importance of maintaining construct boundaries in concise instruments. Stein et al. (2024) further demonstrated the relevance of factor-structure and wording considerations in measuring general AI attitudes. Among pre-service teachers, Aktay et al. (2024) identified dimensions relating to benefits, risks, and use, while Mukherjee and Dasgupta (2024) considered general views, applications, benefits, and concerns. Collectively, these studies show that AI attitude has been operationalised according to different theoretical and contextual assumptions. A comparable issue arises in measuring behavioural intention. Chai et al. (2024), for example, developed an Artificial Intelligence Learning Intention Scale and distinguished behavioural intention to learn AI from other AI-related dispositions. Mishra and Anthony (2024) likewise examined AI and ChatGPT use in academic contexts, demonstrating the importance of

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specifying the activity associated with intended use. An intention to learn AI, use ChatGPT for academic work, and integrate AI into classroom teaching may all reflect technology acceptance, but they represent different behavioural referents. The broader literature reinforces this distinction. Naseri and Abdullah (2024) highlight TAM, the Theory of Planned Behavior, and the Unified Theory of Acceptance and Use of Technology as relevant frameworks for understanding AI adoption in education. Contemporary research also examines perceived usefulness, perceived ease of use, self-efficacy, AI literacy, anxiety, social influence, readiness, and facilitating conditions as factors associated with AI-use intentions (Ayanwale et al., 2024; Liu et al., 2026; Tootkaboni & Maghsoudi, 2025). These variables may explain intention but are conceptually different from intention itself. Similarly, Villaceran and Himang (2025) empirically separated perceived usefulness, perceived ease of use, and intention to use AI Copilot. Research involving pre-service teachers has also situated behavioural intention within specific activities such as lesson planning and teaching (Mnguni et al., 2025; Ramnarain et al., 2025; Wang et al., 2025).

Against this background, the present study focuses on the development and validation of a concise measure of Attitude Toward Use (ATT) and Behavioural Intention to Use (BIU) artificial intelligence in mathematics education among pre-service mathematics teachers. Guided by TAM and informed by contemporary research on AI attitude and behavioural-intention measurement, the study focuses on respondents' evaluations of AI use and their intentions to use AI in mathematics learning and teaching. The resulting instrument is intended to provide a focused measurement foundation for research on AI integration in mathematics teacher education.

Attitude Toward Use (ATT)

ATT represents an individual's evaluation of engaging in a particular technology-use behaviour. In the original TAM, Davis et al. (1989) examined attitude toward using computer technology alongside perceived usefulness, perceived ease of use, behavioural intention, and actual system use. Although their empirical findings led to a more parsimonious TAM in which attitude was not retained as a direct predictor of behavioural intention, the construct remains relevant in research concerned with individuals' evaluations of technology use. Importantly, ATT differs from beliefs about what a technology can provide and from the intention to perform the corresponding behaviour. AI research demonstrates considerable variation in how attitudes are conceptualised. General AI-attitude studies have examined individuals' favourable and unfavourable evaluations of AI, including broader perceptions of its benefits, risks, and implications (Grassini, 2023; Schepman & Rodway, 2020; Sindermann et al., 2021). Such measures provide useful evidence about general orientations toward AI, but they do not necessarily capture evaluations of using AI for a specified educational activity. This distinction becomes more important in teacher education, where attitudes may concern AI generally, its educational applications, or its integration into particular teaching practices.

Studies involving pre-service teachers further illustrate this contextual variation. Guan et al. (2025), for example, examined attitudes toward AI integration alongside AI literacy and self-efficacy, highlighting the conceptual distinction between an individual's evaluation of AI and their knowledge or confidence in using it. Other research has reported relationships between AI-related attitudes and behavioural intention among teachers and pre-service teachers, including pre-service mathematics teachers (Mosia et al., 2026; Qudratuddarsi & Meivawati, 2025). Similar relationships have been reported in other educational and professional contexts (Emon & Khan, 2025; Labrague & Al Harrasi, 2025). However, evidence that attitude is associated with intention does not make the two constructs interchangeable.

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A key issue emerging from the literature is therefore referent specificity. An attitude toward AI in general reflects a broad evaluation of the technology, whereas attitude toward use concerns the evaluation of engaging in a specified technology-use behaviour. For pre-service mathematics teachers, the relevant behaviour involves using AI within mathematics learning and teaching. This may include lesson preparation, mathematical explanation, problem solving, assessment, or instructional resource development. Consequently, general positivity toward AI cannot automatically be interpreted as a positive evaluation of using AI in mathematics education. For the present study, ATT is therefore conceptualised as a focused evaluative construct referring specifically to the use of AI in mathematics learning and teaching. This specification provides a clearer construct boundary than broader measures of general AI attitudes and supports its measurement as a construct distinct from behavioural intention to use AI.

Behavioural Intention to Use (BIU)

Behavioural intention to use (BIU) refers to an individual's intention to perform a specified technology-use behaviour. In technology acceptance research, behavioural intention has been examined as an immediate antecedent of actual system use; Davis et al. (1989), for example, found that behavioural intention was related to subsequent computer use within their comparison of the TAM and the Theory of Reasoned Action. Davis (1989) further established perceived usefulness and perceived ease of use as central beliefs underlying technology acceptance. Together, these foundations distinguish the intention to perform a technology-use behaviour from the beliefs and evaluations that may contribute to that intention. Research involving pre-service teachers similarly demonstrates that behavioural intention is associated with attitudinal and other cognitive determinants of technology use. Teo (2010), for example, reported a substantial influence of attitude toward computer use on pre-service teachers' intention to use technology within an integrated TAM–Theory of Planned Behavior framework. More recent research has extended this relationship to artificial intelligence (AI) within specific educational practices. Ramnarain et al. (2025) found that attitude toward AI use, AI literacy, subjective norm, perceived behavioural control, and perceived usefulness significantly predicted pre-service science teachers' intention to use generative AI in inquiry-based teaching. Mnguni (2025) similarly examined pre-service Life Sciences teachers' intentions to integrate AI into teaching and identified attitudinal, normative, and contextual factors associated with such intentions. These studies indicate that behavioural intention is more meaningfully interpreted when the intended behaviour is explicitly situated within a particular educational context.

Contemporary AI research also demonstrates substantial variation in the factors used to explain behavioural intention. Wang et al. (2025), for instance, integrated TAM, UTAUT, and Expectation-Confirmation Theory to examine pre-service teachers' sustained intention to use ChatGPT, highlighting the roles of social influence and facilitating conditions. Such explanatory models reinforce an important measurement principle: determinants of behavioural intention should not be treated as components of the intention construct itself. Perceived usefulness, social influence, facilitating conditions, AI literacy, perceived behavioural control, and attitude may explain or influence BIU, but they are conceptually different from the intention to perform the behaviour. Behavioural intention must also be distinguished according to its behavioural referent. Intention to learn AI, use AI for lesson planning, employ ChatGPT for academic work, integrate AI into inquiry-based teaching, and use AI for mathematics teaching and learning represent related but non-equivalent intentions (Odai et al., 2024; Tang, 2024; Yurt & Kaşarcı, 2025). For pre-service mathematics teachers, BIU therefore requires a sufficiently specific referent to capture the

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prospective use of AI within mathematics-related learning and teaching activities (Zheng et al., 2025). In the present study, BIU is conceptualised as a focused intention to use and integrate AI tools in mathematics learning and teaching. This specification maintains a clear boundary between behavioural intention and the attitudes, beliefs, capabilities, and contextual conditions that may account for it, providing a coherent basis for its separate measurement from attitude toward use.

Relationship Between ATT and BIU

ATT and BIU are conceptually related but distinct constructs in technology-acceptance research. ATT concerns an individual's evaluation of performing a specified technology-use behaviour, whereas BIU concerns the intention to perform that behaviour. Davis et al. (1989) examined both constructs within their comparison of the TAM and the Theory of Reasoned Action, while subsequent research has demonstrated that their empirical relationship can vary across models and contexts. Thus, although a favourable evaluation of technology use may be associated with stronger behavioural intention, the two constructs should not be treated as interchangeable. Evidence from educational settings supports an association between attitudes and behavioural intention. Teo (2010), for example, reported that attitude toward computer use substantially influenced pre-service teachers' intention to use technology within an integrated TAM–Theory of Planned Behavior framework. Gurer (2021) similarly found that attitudes toward technology were associated with intention among pre-service mathematics teachers. More recent AI-focused studies have reported comparable relationships. Sun et al. (2025) identified attitude as an important determinant of pre-service teachers' intention to use generative AI, while Ramnarain et al. (2025) reported a significant relationship between attitudes toward AI and intention to integrate generative AI into inquiry-based teaching. In the Nigerian higher-education context, Zakariya et al. (2026) likewise found that students' attitudes toward computer-based testing were related to, but distinguishable from, their conditional intention to continue using the technology.

The distinction between ATT and BIU is particularly important for measurement because factors associated with intention are not necessarily indicators of intention. Perceived usefulness, perceived ease of use, self-efficacy, social influence, facilitating conditions, and AI literacy may contribute to the formation of behavioural intention, but each represents a conceptually different construct. Likewise, a favourable attitude toward AI does not necessarily imply an intention to use AI for a particular educational purpose. The behavioural referent must therefore remain explicit when both constructs are measured. Accordingly, the present study specifies ATT as an evaluative response toward using AI in mathematics learning and teaching, while BIU represents the intention to use or integrate AI within those activities. This distinction provides the conceptual basis for developing separate indicators for the two constructs and helps prevent the conflation of evaluation, intention, and the factors that may influence technology adoption.

Research Methodology

Research Design

The study adopted a quantitative cross-sectional survey design to develop and validate a concise measure of pre-service mathematics teachers' ATT and BIU, AI in mathematics teaching and learning. Data were collected at a single point in time using a structured questionnaire. The analysis focused on evaluating the measurement properties of the two theoretically distinct constructs within the TAM, with particular attention to their factor structure and reliability.

Study Context and Participants

The study was conducted among pre-service mathematics teachers enrolled in three higher institutions in the Federal Capital Territory (FCT), Abuja, Nigeria: a university, a college of education,

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and an open higher institution. The institutions were selected to represent different forms of higher education and teacher preparation within the study context. The sample comprised 221 pre-service mathematics teachers, including 71 (32.1%) from the university, 73 (33.0%) from the college of education, and 77 (34.8%) from the open higher institution. By gender, 109 (49.3%) participants were male and 112 (50.7%) were female. Eligibility was restricted to students enrolled in mathematics teacher education programmes in the participating institutions.

Instrument Development

The development process was guided by the TAM and informed by relevant theoretical and empirical literature on technology acceptance, attitudes toward artificial intelligence, and behavioural intentions to use AI in educational contexts. The development procedure followed a sequential process comprising: (1) theoretical specification of the constructs; (2) generation of candidate items; (3) expert evaluation and preliminary content validation; (4) revision of the candidate items; (5) administration of the revised questionnaire; (6) empirical examination of the measurement structure using confirmatory factor analysis (CFA); (7) item evaluation and theoretically justified model refinement; and (8) assessment of the reliability of the resulting scales. The items were therefore treated as theory- and literature-informed indicators requiring empirical evaluation rather than as automatically valid measures.

Theoretical Specification of the Constructs

The operational definitions of ATT and BIU established in the preceding conceptual framework were used as the basis for item development. ATT was operationalised as respondents' overall dispositions towards the use of AI in mathematics teaching and learning, whereas BIU was operationalised as their intention to use or integrate AI in mathematics teaching and learning. The items were generated deductively from the TAM and relevant empirical literature. During item development, attention was given to maintaining clear boundaries between the two target constructs and related technology-acceptance variables. Candidate ATT items were required to represent respondents' evaluations or affective orientations toward AI use, while candidate BIU items were required to represent future-oriented intentions to use or integrate AI in mathematics teaching and learning. Antecedent beliefs, capabilities, and contextual conditions were not intended to serve as indicators of ATT or BIU. The theoretical specification therefore provided the conceptual criteria against which candidate items were subsequently evaluated for relevance, clarity, behavioural specificity, and construct alignment.

Item Generation

An initial pool of eight candidate items was generated deductively from the operational definitions of ATT and BIU and informed by the relevant theoretical and empirical literature. At this stage, four items were specified for ATT and four items for BIU. The candidate items were designed to capture respondents' evaluations of AI use and their future-oriented intentions to use AI in mathematics teaching and learning.

The initial ATT items were:

1. ATT01: Using AI in Mathematics education is a good idea.
2. ATT02: I have a positive attitude toward using AI in Mathematics learning and teaching.
3. ATT03: Using AI in Mathematics education would be beneficial.
4. ATT04: I enjoy the idea of using AI for Mathematics learning.

The initial BIU items were:

1. BIU01: I intend to use AI tools in learning and teaching Mathematics in the future.

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2. BIU02: I will regularly use AI tools for Mathematics-related tasks.
3. BIU03: I plan to integrate AI tools into my future Mathematics teaching.
4. BIU04: I would recommend the use of AI tools for Mathematics education.

The candidate items were subsequently subjected to expert evaluation before empirical administration. During this process, particular attention was paid to potential conceptual overlap among items and related constructs. For example, an item referring to the benefits of AI could potentially reflect perceived usefulness rather than attitude alone, while an item referring to recommending AI could represent a social or advocacy response rather than the respondent's own behavioural intention. These considerations informed the subsequent evaluation and empirical assessment of the items.

Data Collection and Analysis

Data were collected from pre-service mathematics teachers enrolled in the three participating higher institutions in FCT, Abuja. Following the necessary institutional permissions, the researchers visited the participating institutions and administered the questionnaires directly to eligible participants using a paper-based format. Before administration, participants were informed about the purpose of the study, the voluntary nature of participation, and the confidentiality of the information provided. They were also informed that participation was solely for research purposes and would have no consequences for their academic standing. Clear instructions were provided to facilitate accurate completion of the questionnaire. Completed questionnaires were collected immediately after administration and screened for completeness and suitability for analysis. A total of 221 valid questionnaires were retained for statistical analysis. The responses were subsequently coded and entered into the statistical software for analysis. The data were analysed using procedures appropriate for scale development and validation. Preliminary data screening was conducted before assessment of the measurement models. The factor structure of the ATT and BIU scales was examined using latent-variable modelling, while scale reliability was assessed using McDonald's coefficient omega (ω).

Presentation of Results

Measurement Model of Attitude Toward Use

The measurement structure of the Attitude Toward Use (ATT) construct was examined using a one-factor latent-variable model in which the observed ATT items were specified as indicators of a common underlying construct. The initial specification (Model 1) demonstrated inadequate fit to the observed data, $x^2(5) = 55.271$, $p < .001$, RMSEA = .213, 90% CI [.165, .266], CFI = .854, TLI = .707, and SRMR = .069. The pattern of fit indices indicated substantial discrepancy between the hypothesised measurement structure and the observed response covariance matrix, particularly as reflected in the low CFI and TLI and elevated RMSEA. Item-level examination identified ATT01 as having a relatively weak standardized factor loading of .370. The item was therefore removed from the measurement model. Examination of the residual structure subsequently indicated an association between the errors of ATT04 and ATT05, which was specified in the revised model on substantive and measurement grounds. The resulting Model 2 was then evaluated using the same fit criteria.

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Table 1

The goodness of fit statistics for one-factor ATT scale

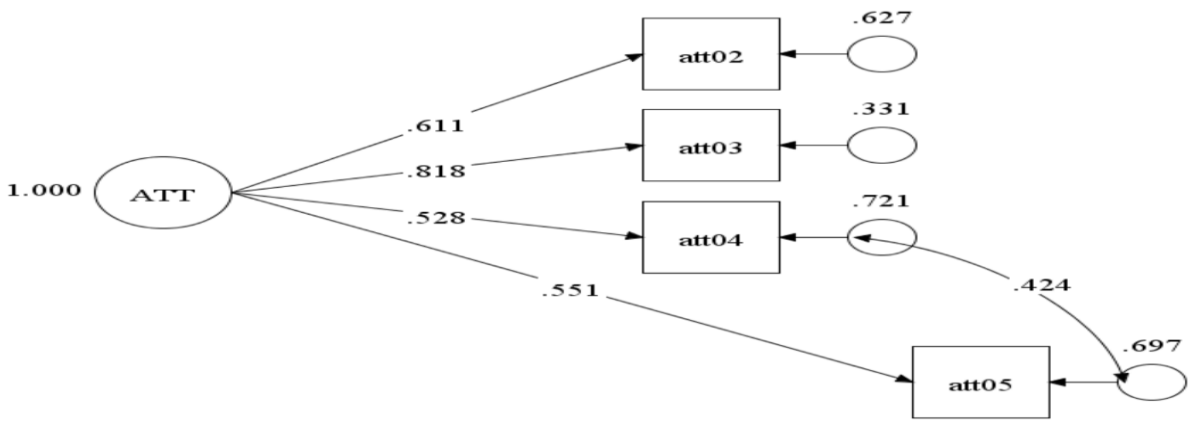
Global fit statistics	Model 1	Model 2
Chi-square		
Estimate (χ^2)	55.271	4.187
Degrees of freedom (df)	5	1
p-value	<.001	0407
χ^2 / df	11.0542	4.187
RMSEA (Root Mean Square Error of Approximation)		
Estimate	.213	.120
90 percent confidence interval	[.165, .266]	[.020, .248]
Probability RMSEA <= .05	<.001	.099
CFI/TLI		
CFI (Comparative Fit Index)	.854	.990
TLI (Tucker-Lewis index)	.707	.938
SRMR (Standardized Root Mean Square Residual)	.069	.019

The revised model showed a substantial improvement in fit relative to Model 1. The chi-square statistic decreased from 55.271 to 4.187, while CFI increased from .854 to .990 and TLI from .707 to .938. SRMR decreased from .069 to .019, indicating substantially lower standardized residual discrepancy. RMSEA also declined from .213 to .120, although the revised estimate remained above the conventional threshold for close approximate fit. The 90% confidence interval for RMSEA was [.020, .248], indicating uncertainty around the approximate-fit estimate. Overall, the revised specification provided a markedly better representation of the observed data than the initial model, particularly according to the comparative and residual fit indices.

The standardized parameter estimates for the revised ATT measurement model are presented in Figure 3.

Figure **1**

Standardised estimates of model parameters for the 1-factor ATT scale



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Figure 3 presents the standardized parameter estimates for the revised one-factor ATT measurement model. All four retained indicators demonstrated positive factor loadings on the latent ATT construct, ranging from .528 to .818. The strongest loading was observed for att03 (λ = .818), followed by att02 (λ = .611), att05 (λ = .551), and att04 (λ = .528). Thus, each retained item demonstrated a meaningful relationship with the underlying ATT construct, although the magnitude of association varied across indicators. The corresponding standardized residual variances were .627, .331, .721, and .697, respectively, indicating that the latent factor accounted for approximately 37.3%, 66.9%, 27.9%, and 30.4% of the variance in att02, att03, att04, and att05. A residual covariance of .424 was specified between att04 and att05, indicating shared item-specific variance beyond that explained by the common ATT factor. Overall, the standardized estimates support the retention of the four indicators, while also indicating that att04 and att05 contain some residual covariance that should be considered when interpreting the revised measurement structure.

Measurement Model of Behavioural Intention to Use

The Behavioural Intention to Use (BIU) scale was evaluated using a one-factor latent-variable model, with the observed items specified as indicators of a common underlying intention to use or integrate AI in mathematics teaching and learning. The model yielded $x^2(5) = 11.455$, $p = .043$, with a x^2/df ratio of 2.291. The corresponding fit indices were RMSEA = .076, 90% CI [.013, .136], CFI = .986, TLI = .972, and SRMR = .025.

Table **2**.

The goodness of fit statistics for one-factor BIU scale

Global fit statistics	Model Statistics
Chi-square	
Estimate (χ^2)	11.455
Degrees of freedom (df)	5
p-value	.0431
χ^2 / df	2.291
RMSEA (Root Mean Square Error of Approximation)	
Estimate	.076
90 percent confidence interval	[.013, .136]
Probability RMSEA <= .05	.188
CFI/TLI	
CFI (Comparative Fit Index)	.986
TLI (Tucker-Lewis index)	.972
SRMR (Standardized Root Mean Square Residual)	.025

The results indicated that the one-factor BIU model provided an adequate representation of the observed data. Although the chi-square test was statistically significant, the comparative fit indices were high, with CFI = .986 and TLI = .972. The SRMR of .025 indicated low standardized residual discrepancy, while the RMSEA of .076 suggested acceptable approximate fit. Taken together, the pattern of fit statistics supported the proposed unidimensional measurement structure of BIU. The standardized parameter estimates for the BIU measurement model are presented in Figure 4.

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Figure **2**

Standardised estimates of model parameters for the one-factor BIU scale

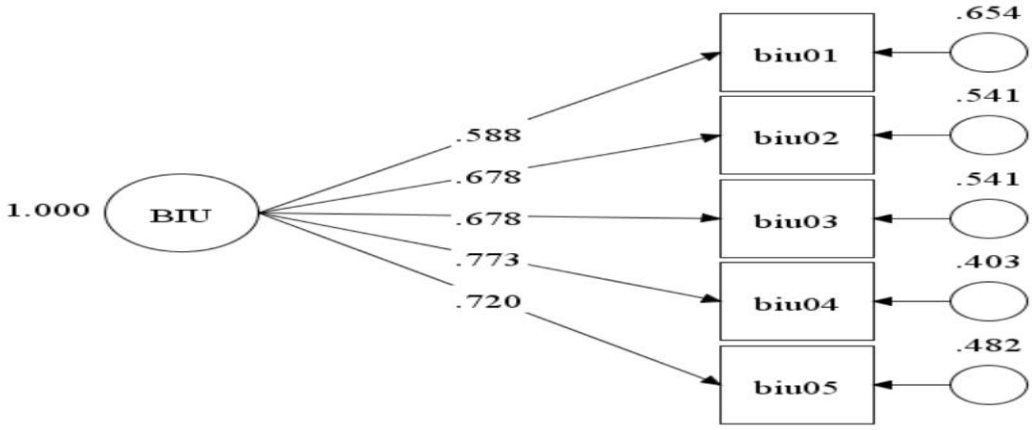


Figure 4 presents the standardized parameter estimates for the one-factor BIU measurement model. All five indicators demonstrated positive and substantive factor loadings on the latent BIU construct, ranging from .588 to .773. The strongest loading was observed for biu04 (λ = .773), followed by biu05 (λ = .720), while biu02 and biu03 both loaded at .678 and biu01 at .588. These estimates indicate that all retained indicators made meaningful contributions to the measurement of behavioural intention to use AI. The corresponding standardized residual variances were .654, .541, .541, .403, and .482, indicating that the BIU factor explained approximately 34.6%, 45.9%, 45.9%, 59.7%, and 51.8% of the variance in biu01 through biu05, respectively. No residual covariances were specified, suggesting that the covariance among the indicators was adequately represented through the common BIU factor. Taken together, the standardized estimates provide support for the proposed unidimensional structure of the BIU-AI scale.

Discussion of Findings

This study developed and evaluated a concise measure of Attitude Toward Use (ATT) and Behavioural Intention to Use (BIU) artificial intelligence among pre-service mathematics teachers. The findings provide initial evidence that the two constructs can be represented as distinct, theoretically bounded dimensions of AI acceptance. The BIU model demonstrated stronger overall measurement performance, while the ATT model showed substantial improvement after item refinement, although its RMSEA remained above the conventional criterion for close fit.

Attitude Toward Use

The initial ATT model demonstrated inadequate fit, but the revised model showed substantial improvement, with CFI increasing from .854 to .990, TLI from .707 to .938, and SRMR decreasing from .069 to .019. The four retained indicators loaded positively on ATT, with loadings ranging from .528 to .818, indicating that each item contributed meaningfully to the latent construct. These findings provide qualified support for measuring attitude toward AI use as a unidimensional construct. The result is consistent with previous AI-attitude research demonstrating that attitudes toward AI can be measured through a relatively concise set of evaluative indicators (Schepman & Rodway, 2020; Sindermann et al., 2021; Grassini, 2023). However, the present scale differs conceptually from general AI-attitude measures because its referent is AI use in mathematics teaching and learning. This distinction is important because an individual may hold a favourable

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view of AI generally without necessarily evaluating its use positively within mathematics education. The ATT findings nevertheless require cautious interpretation. Although the revised model produced strong CFI, TLI, and SRMR values, RMSEA remained relatively high at .120. Moreover, a residual covariance was specified between att04 and att05, suggesting some shared variance beyond the general ATT factor. Thus, the revised model represents a substantial improvement over the initial specification, but should not be described as demonstrating unequivocally close fit. Replication with an independent sample is necessary to determine whether this structure is stable.

Behavioural Intention to Use

The BIU model demonstrated a stronger measurement profile. The one-factor model produced high CFI (.986) and TLI (.972), low SRMR (.025), and an RMSEA of .076, indicating acceptable approximate fit. All five indicators loaded substantially on the latent construct, ranging from .588 to .773, while the reliability coefficient was satisfactory (ω = .786). The absence of correlated residuals further supports a relatively straightforward unidimensional representation of BIU. This finding is consistent with TAM, which positions behavioural intention as a proximal construct reflecting an individual's intention to perform a specified technology-use behaviour (Davis, 1989; Davis et al., 1989). It also complements recent research on AI use among pre-service teachers, where behavioural intention has been examined in relation to lesson planning, teaching, and other educational applications (Wang et al., 2024; Ramnarain et al., 2025). The present study extends this work by defining the behavioural referent specifically around AI use in mathematics teaching and learning. Importantly, the findings support a distinction between measuring BIU and explaining BIU. Contemporary studies often incorporate perceived usefulness, self-efficacy, AI literacy, social influence, facilitating conditions, and related variables to explain intention (Ayanwale et al., 2024; Tootkaboni & Maghsoudi, 2025; Zhang et al., 2026). These variables may influence BIU but should not automatically be treated as indicators of the construct itself. The present scale therefore provides a more focused operationalisation of intention.

Implications for Measurement

Taken together, the findings support the theoretical distinction between ATT and BIU. ATT captures an individual's evaluation of using AI, whereas BIU captures the intention to engage in that behaviour. Although these constructs are theoretically related and previous studies have shown that attitude can predict intention (Teo, 2010; Gurer, 2021; Sun et al., 2025), the present study did not estimate a structural relationship between them. Its purpose was instead to establish focused measurement models for each construct. This distinction has practical implications for AI research in mathematics teacher education. A concise instrument can be useful where researchers need to assess specific acceptance constructs without introducing unnecessary dimensions. The findings therefore support the use of construct-specific measurement rather than broad acceptance instruments that combine attitudes, beliefs, capabilities, and contextual factors. The reliability coefficients obtained for ATT (ω = .715) and BIU (ω = .786) further indicate that the scales provide acceptable reliability despite their concise structure (Zakariya & Massimiliano, 2022).

Limitations and Future Research

The study has several limitations. The sample comprised 221 pre-service mathematics teachers from three higher institutions in FCT, Abuja, limiting generalisability beyond the study context. The validation also relied on a single cross-sectional sample; therefore, the reported structure requires replication and cross-validation with independent samples. Future studies should examine convergent, discriminant, and criterion-related validity and test whether the scales demonstrate measurement invariance across relevant groups. In addition, BIU represents intended, rather than

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actual, AI use. Longitudinal research should therefore examine whether BIU predicts subsequent AI integration in mathematics teaching. Future research should also investigate how perceived usefulness, ease of use, AI literacy, self-efficacy, trust, and contextual conditions relate to the two constructs without incorporating these variables into their measurement.

Conclusion

The study provides initial evidence for a concise measure of ATT and BIU toward AI use in mathematics teaching and learning among pre-service mathematics teachers. The BIU scale demonstrated a stronger and more coherent measurement structure, while the ATT scale showed substantial improvement following refinement but warrants further validation. Overall, the findings support a theoretically bounded approach in which attitude and behavioural intention are measured as distinct constructs rather than as a broad, undifferentiated form of AI acceptance.

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