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Preservice mathematics teachers' AI adoption intentions: Examining the roles of awareness, trust, and risk

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Abstract
Artificial intelligence (AI) adoption among preservice mathematics teachers remains uneven. This study aimed to identify adoption predictors, test trust mediation, examine risk moderation, compare demographic subgroups, and evaluate a sequential awareness-ease-usefulness-trust-intention model. Survey data from 130 South African preservice mathematics teachers were analyzed using regression, mediation, moderation, subgroup analysis, and structural equation modelling. Trust (β = .38), usefulness (β = .26), and awareness (β = .19) positively predicted intention; risk predicted it negatively (β = -.16), while ease had no direct effect. Trust partially mediated all cognitive pathways (44.2%-58.5%), and risk weakened the usefulness-, trust-, and awareness-intention relationships. Usefulness was strongest for men, trust for women, and explained variance was greater in years 3-4 than years 1-2 (64.8% vs. 52.4%). The sequential model had acceptable fit and a significant full indirect effect (0.031, 95% confidence interval [0.009, 0.061]).

Keywords: artificial intelligence adoption, awareness of AI tools, perceived risk and trust, preservice mathematics teachers, structural equation modelling

INTRODUCTION

The rapid development of advanced generative and curriculum-focused artificial intelligence (AI) tools has placed teacher education at a critical crossroads. Educational institutions are now tasked with equipping future educators not only to utilize technology but also to teach responsibly with systems that increasingly shape learning, assessment, and classroom decision-making. Policy reports and sector reviews therefore stress the need for swift, system-wide integration of AI into curricula and professional training. This enables teachers to harness AI's pedagogical potential while carefully managing ethical, privacy, and instructional risks (U.S. Department of Education, 2023; Vincent-Lancrin & van der Vlies, 2020). Within mathematics education, many of these AI applications function as AI-driven objects-to-think-with, that is, interactive digital artefacts such as intelligent tutors, generative problem solvers, adaptive visualization tools, and feedback systems that support learners' cognitive engagement, reasoning, and conceptual understanding. Rather than serving merely as automation tools, these AI systems act as mediational resources that externalize thinking, support exploration of mathematical representations, and scaffold problem-solving processes (Son, 2024). For preservice mathematics teachers, adopting AI-driven objects-to-think-with requires not only technical familiarity but also pedagogical judgement about how such tools align with mathematical reasoning, epistemological beliefs, and instructional goals.

Decades of research grounded in the technology acceptance model (TAM) (Davis, 1989) and its extensions demonstrate that perceived usefulness (PU) and perceived ease of use (PEOU) remain robust predictors

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Contribution to the literature

- This study extends the TAM by integrating cognitive, affective, and risk-related mechanisms within a single model of preservice mathematics teachers' AI adoption.
- It demonstrates that trust mediates awareness, ease-of-use, and usefulness pathways, whereas perceived risk weakens key effects on intention. It also identifies gender- and year-level variation in predictor importance and validates a sequential awareness-ease-usefulness-trust-intention pathway.
- The findings offer context-sensitive evidence for designing AI preparation in mathematics teacher education.

of educators' behavioral intention to adopt educational technologies. Recent TAM-based studies focusing on AI have reaffirmed the salience of these cognitive appraisals among both in-service and preservice teachers (Alejandro et al., 2024; Sanusi et al., 2024). In the context of AI-driven objects-to-think-with, usefulness reflects teachers' beliefs that AI meaningfully enhances mathematical understanding and teaching effectiveness, while ease of use captures perceptions of cognitive and instructional effort required to integrate such tools into practice.

Concurrently, a growing body of empirical evidence highlights affective and socio-technical variables, particularly trust and perceived risk, as critical determinants of educators' acceptance of AI-enabled technologies (Nazaretsky et al., 2025; Viberg et al., 2025). These studies suggest a complex acceptance process in which awareness and competence shape judgements of usefulness, while concerns about accuracy, bias, transparency, and data privacy influence willingness to rely on AI systems in instructional contexts. For AI-driven objects-to-think-with, trust becomes especially salient because teachers must depend on the correctness, pedagogical alignment, and ethical integrity of AI-generated representations and feedback. Despite these advances, the precise interaction of cognitive (awareness, PEOU, and PU), affective (trust), and barrier (perceived risk) dimensions within a coherent explanatory framework remains underexplored among preservice mathematics teachers. This population has received limited attention in quantitative, model-based research, even though their disciplinary orientation and reliance on representational tools may uniquely shape how they evaluate AI-driven learning environments. Existing empirical and review studies have often examined trust or risk in isolation and predominantly relied on basic regression approaches rather than testing sequential mediation and moderation mechanisms using structural equation modelling (SEM) (Kuzu, 2025; Laru et al., 2025). Moreover, few reviews have explicitly examined whether perceived risk weakens or nullifies the positive effects of awareness, usefulness, or trust on behavioral intention among preservice teachers.

These gaps hinder the development of teacher education interventions that simultaneously build AI-related competence, foster trust in AI-driven objects-to-think-with and mitigate perceived risks. Responding to this need, the present SEM study proposes an augmented TAM framework that models a sequential pathway from AI awareness to PEOU, PU, trust, and behavioral intention, while simultaneously examining perceived risk as a moderating influence. By focusing specifically on preservice mathematics teachers, this study advances domain-sensitive evidence on how future educators evaluate and intend to adopt AI-driven objects-to-think-with in mathematics teaching and learning.

REVIEW OF RELATED EMPIRICAL LITERATURE

In this section, we review related empirical studies that focused on the constructs and relationships driving this study. These constructs include TAM foundations, AI awareness, trust, perceived risk, preservice teachers, and methods.

Traditional TAM Constructs in Technology Acceptance

The TAM identifies PU and PEOU as key predictors of technology adoption. Systematic reviews and meta-analyses consistently show that these constructs robustly predict behavioral intention across educational contexts, with extended TAM models retaining PU-PEOU relationships while incorporating context-specific factors (Kelly et al., 2023; Scherer et al., 2019). Within teacher education, SEM studies confirm that PEOU positively influences PU, which in turn predicts behavioral intention (Antonietti et al., 2022; Lin & Yu, 2023). Evidence from the COVID-19 period further supports this pathway in practice. For example, Dindar et al. (2021) found that prior experience strengthened the PEOU → PU → intention relationship. Antonietti et al. (2022) showed that teachers' digital competence enhanced both PEOU and PU, increasing adoption intention.

However, AI-specific studies suggest that while TAM remains relevant, its explanatory power is conditioned by contextual and affective factors. Perceived risks and emotional responses can weaken TAM relationships (Wu et al., 2022), and AI awareness interacts with expectancy beliefs in shaping adoption (Milicevic et al., 2024). Thus, while PU and PEOU remain essential, AI adoption requires extending TAM within broader socio-technical frameworks that account for uncertainty, autonomy, and trust, particularly in teacher education contexts where pedagogical and ethical considerations are central. Related South African evidence also shows that TPACK-related knowledge domains predict preservice mathematics and science teachers' technology integration (Mosia & Matabane, 2022).

AI Awareness and Cognitive Appraisal Pathways

AI-specific awareness extends beyond general digital familiarity to include understanding AI's data-driven, probabilistic, and opaque nature, as well as its ethical and pedagogical implications. In education, this involves the ability to interpret AI-generated outputs and integrate them into teaching, particularly when using AI-driven objects-to-think-with.

Empirical studies position AI awareness as an upstream cognitive antecedent shaping PEOU and PU, thereby influencing adoption intentions (Kuzu, 2025; Milicevic et al., 2024; Nazaretsky et al., 2025). Beyond cognition, awareness also supports affective processes and predicts trust in AI (Viberg et al., 2025). It also enhances behavioral intention through usefulness and motivation (Acquah et al., 2024; Liu, 2025). These findings support the role of awareness as a precursor to both cognitive and affective pathways. However, prior research rarely tests these pathways simultaneously or sequentially using SEM, especially among preservice mathematics teachers. Additionally, most studies assume uniformly positive effects of awareness, without accounting for limiting conditions. This highlights the need to examine moderating factors, particularly perceived risk, that may constrain the translation of cognitive and affective appraisals into adoption intention.

Trust in AI as an Affective and Mediating Mechanism

Prior empirical studies consistently identify trust as a central affective mechanism shaping AI adoption in educational contexts, particularly in linking cognitive appraisals to behavioral intention. In AI-driven educational technologies, trust reflects users' confidence in the reliability, transparency, and ethical operation of AI systems (Viberg et al., 2025). Empirical evidence shows that trust strengthens the translation of PU and AI awareness into adoption intention. For example, Nazaretsky et al. (2025) found that higher trust increased educators' willingness to use AI-driven objects-to-think-with beyond the effects of PU. Cui et al. (2025) showed through meta-analysis that trust mitigates the negative influence of perceived risk on AI adoption intentions. Cross-national findings further show that AI awareness and perceived benefits significantly predict trust, which in turn directly predicts intention to adopt AI in education (Viberg et al., 2025).

Despite these findings, prior studies have not systematically tested trust as a mediator linking AI awareness, PEOU, and PU to adoption intention within a single model. Existing research often examines trust as a direct predictor or partial mediator, without modelling its position within a sequential cognitive-affective pathway. Although Zhang et al. (2025) showed that trust mediates the relationship between PEOU and intention, upstream awareness and downstream risk effects were not simultaneously examined. Consequently, it remains unclear whether trust operates as a consistent mediating mechanism across multiple appraisal stages. Aligned with these gaps, the present study explicitly hypothesizes that trust mediates the relationships between

(a) AI awareness,

(b) PEOU,

(c) PU, and adoption intention among preservice mathematics teachers.

By testing these mediation pathways using SEM, the study advances prior work by clarifying the precise affective role of trust within an integrated AI adoption framework.

Perceived Risk and Moderation Effects

Perceived risk has emerged as a critical factor shaping the adoption of AI-integrated technologies in education. In this study, perceived risk refers to individuals' awareness of potential negative consequences associated with AI use, including data privacy violations, algorithmic bias, ethical ambiguity, and threats to professional autonomy (Cui et al., 2025). While early TAMs primarily emphasized cognitive evaluations such as PU and usability, more recent research recognizes that risk perceptions can directly suppress adoption intentions and weaken the influence of positive determinants such as trust and PU.

Empirical evidence supports this moderating role of perceived risk in AI adoption. Wu et al. (2022) found that heightened risk perceptions impeded AI adoption among educators and preservice instructors by reducing effort expectancy and diminishing the impact of favorable cognitive appraisals on behavioral intention. Similarly, Zhang et al. (2025) reported that privacy and safety concerns undermined preservice teachers' trust in AI tutoring systems, thereby lowering their readiness to use such tools. Rana et al. (2024) further showed that ethical and data security concerns weakened the relationship between PU and intention to adopt AI-driven assessment systems among university lecturers. Notably, Zhang et al. (2025) also provided evidence that perceived risk moderates the trust-intention relationship. This suggests that even high trust may not translate into adoption when perceived risks remain salient. Despite these advances, prior studies have predominantly modelled perceived risk as a direct predictor rather than explicitly testing its moderating effects within comprehensive adoption frameworks. In particular, few studies have examined whether perceived risk systematically alters the strength of the trust → intention or usefulness → intention pathways using SEM, especially among preservice teachers. Addressing this unresolved issue, the present study explicitly hypothesizes that perceived risk moderates key relationships within the AI adoption model, thereby clarifying its conditional role in shaping preservice mathematics teachers' adoption intentions.

Methodological Gaps and Domain-Specific Population Focus

Despite advances using TAM and UTAUT frameworks, methodological limitations persist in AI adoption research, including reliance on cross-sectional designs and convenience samples, which constrain generalizability (Kelly et al., 2023). Many studies employ basic regression approaches rather than SEM. This limits the analysis of complex mediation and moderation effects (Zhang et al., 2025). These limitations hinder deeper understanding of trust, perceived risk, and awareness pathways. Furthermore, research largely focuses on general teacher populations or students in IT and business, with limited attention to preservice mathematics teachers (Alissa & Hamadneh, 2023; Viberg et al., 2025). Given the abstract and representational nature of mathematics, this group may exhibit distinct cognitive and affective responses to AI, including sensitivity to bias and the validity of AI-generated explanations (Milicevic et al., 2024). Existing literature also shows scarcity of longitudinal and context-sensitive studies capturing how AI perceptions evolve across teacher education and within resource-constrained contexts (Cui et al., 2025; Rana et al., 2024). This study addresses these gaps by focusing on preservice mathematics teachers and employing SEM to model cognitive, affective, and risk-related factors in AI adoption. Recent South African work has begun to narrow this population gap. Mosia and Nannim (2026) found that the pathway from prior AI training to adoption intention through self-efficacy varied by gender and training status among preservice mathematics teachers, while Mosia et al. (2026) linked AI-TPACK readiness to prior AI use, critical-ethical appraisal, and support/enablers. These studies did not integrate AI awareness, PEOU, PU, trust, and perceived risk within the sequential moderated-mediation framework tested here.

Theoretical Framework and Model Development

This study is theoretically framed on the TAM (Davis, 1989). It is extended using affective and socio-technical perspectives to account for the distinctive properties of AI in education. TAM posits that PEOU influences PU, which in turn predicts behavioral intention. These relationships form the cognitive backbone of the proposed model. Given the complexity, opacity, and ethical implications of AI systems, cognitive evaluations alone are insufficient to explain adoption decisions. Accordingly, AI awareness is theorized as an upstream antecedent that shapes users' ability to evaluate AI tools meaningfully. Higher awareness of AI capabilities and limitations is expected to enhance perceptions of ease of use and usefulness, and to directly influence adoption intention.

Beyond cognition, trust in AI is introduced as a central affective mechanism that translates cognitive appraisals into behavioral intentions. Trust reflects confidence in AI systems' reliability, fairness, and pedagogical value. Trust is hypothesized to mediate the effects of AI awareness, PEOU, and PU on adoption intention. Finally, perceived risk is conceptualised as a socio-technical barrier that conditions adoption decisions. Concerns related to privacy, bias, and professional autonomy are expected not only to reduce intention directly but also to weaken the positive effects of awareness, usefulness, and trust in intention. Based on this framework, the study hypothesizes that

(a) TAM and AI-specific constructs directly predict adoption intention,

(b) trust in AI mediates the relationships between cognitive appraisals and intention,

(c) perceived risk moderates key adoption pathways, and

(d) a sequential mediation pathway—AI awareness → PEOU → PU → trust → adoption intention, adequately explains preservice mathematics teachers' AI adoption intention (**Figure 1**).

Research Questions

The following research questions (RQs) were raised to guide the study:

RQ1: Which of the following variables significantly predict preservice mathematics teachers' adoption intention of AI tools:

(a) PU,

(b) PEOU,

(c) AI awareness,

(d) trust in AI, and

(e) perceived risk?

RQ2: Does trust in AI mediate the relationships of

(a) AI awareness,

(b) PEOU, and

(c) PU with adoption intention?

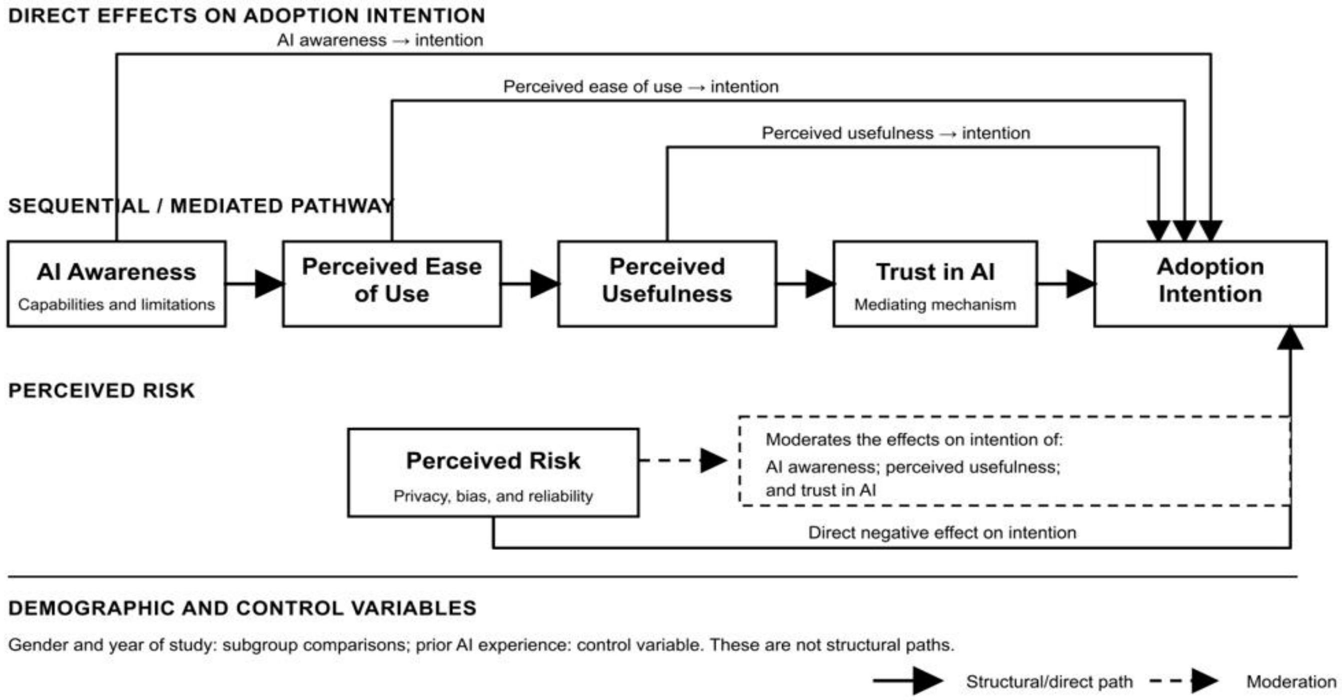

Figure 1. Hypothesized structural model of preservice mathematics teachers' AI adoption intention (dashed arrows: moderation effects; solid arrows: direct or mediating effects; gender and year of study were examined through subgroup analysis, whereas prior AI training was included as a control variable [these are not structural paths]) (the authors' own work)

RQ3: Does perceived risk moderate the relationships of

(a) PU,

(b) trust in AI, and

(c) AI awareness with adoption intention?

RQ4: How do the relative contributions of TAM constructs (PEOU and PU) compare with those of AI-specific constructs (AI awareness, trust in AI, and perceived risk) across gender and year-of-study subgroups?

RQ5: Does a sequential mediation model: AI awareness → PEOU → PU → trust in AI → adoption intention, adequately explain preservice mathematics teachers' AI adoption intention?

Research Objectives

Accordingly, the study pursued the following five objectives:

Objective 1: To identify whether PU, PEOU, AI awareness, trust in AI, and perceived risk significantly predict preservice mathematics teachers' intention to adopt AI tools.

Objective 2: To determine whether trust in AI mediates the relationships of AI awareness, PEOU, and PU with adoption intention.

Objective 3: To assess whether perceived risk moderates the relationships of PU, trust in AI, and AI awareness with adoption intention.

Objective 4: To compare the relative contributions of traditional TAM constructs and AI-specific constructs across gender and year-of-study subgroups.

Objective 5: To test whether the sequential pathway from AI awareness through PEOU, PU, and trust in AI to adoption intention adequately explains preservice mathematics teachers' AI adoption intention.

METHOD

Research Design

This study adopted the quantitative research method, specifically, the cross-sectional, correlational survey research design. In this design, we combined classical TAM constructs, such as PU and PEOU, with AI-specific constructs, including AI awareness, trust in AI, and perceived risk. This provided a full picture of how ready preservice teachers are to adopt AI. The quantitative approach enabled us to rigorously examine direct effects, mediation pathways, moderation effects, and sequential interactions across variables via hierarchical regression, mediation analysis, moderation analysis, and SEM.

Participants

The sample comprised 130 preservice mathematics teachers enrolled in teacher education programs at the University of the Free State, South Africa. It comprised 46 males (35.4%) and 84 females (64.6%). Participants were distributed across four year levels: year 1 (n = 36, 27.7%), year 2 (n = 34, 26.2%), year 3 (n = 31, 23.8%), and year 4 (n = 29, 22.3%). Age ranged from 18 to 26 years (mean [M] = 21.2, standard deviation [SD] = 1.8). Of this sample, 55 (42.3%) participants reported having received formal prior AI training or coursework, while 75 (57.7%) reported no formal AI training experience.

Eligibility was restricted to students currently enrolled in mathematics education programs who had completed at least one semester of study. Students were excluded if they had not used any form of educational technology during their program, ensuring foundational familiarity with technology-enhanced instruction. All participants provided informed consent. The study received ethical approval from the University of the Free State Institutional Review Board, South Africa (clearance no. UFS-HSD2019/0217/3007/22/4/5).

Measures

All constructs were measured using validated multi-item scales adapted from established instruments in technology acceptance and educational technology research. Items employed 5-point Likert scales ranging from 1 (*strongly disagree*) to 5 (*strongly agree*), except where noted. Reliability analyses confirm internal consistency for all scales (Cronbach's $\alpha > .80$ for all measures).

Traditional TAM Constructs

PU was measured using six items adapted from Davis (1989), assessing the degree to which preservice teachers believed AI-driven objects-to-think-with would enhance their teaching effectiveness (e.g., "Using AI tools would improve my ability to teach mathematical concepts," "AI-driven objects-to-think-with would make me a more effective mathematics teacher"). Cronbach's α = .87. PEOU was assessed with five items from Davis (1989), measuring participants' perceptions of the effort required to use AI tools (e.g., "Learning to use AI tools would be easy for me," "I would find AI-driven objects-to-think-with easy to integrate into my lessons"). Cronbach's α = .84. Adoption Intention was measured using four items reflecting behavioral intentions to use AI tools in future teaching practice (e.g., "I intend to use AI-driven objects-to-think-with when I become a teacher," "I plan to integrate AI tools into my mathematics instruction"). Cronbach's α = .89.

Extended Constructs: AI-Specific Variables

AI Awareness was measured using a seven-item scale developed for this study, assessing participants' knowledge and familiarity with AI technologies and their educational applications (e.g., "I am aware of how AI can be used in mathematics education," "I understand the basic capabilities of AI-driven educational tools"). Cronbach's α = .86. Trust in AI was assessed using six items adapted from McKnight et al. (2002) and Gefen et al. (2003), measuring confidence in AI systems' reliability, accuracy, and ethical operation (e.g., "I trust that AI tools would provide accurate mathematical information," "I believe AI-driven learning objects would act in students' best interests"). Cronbach's α = .91. Perceived risk was measured using a five-point rating-scale instrument adapted from Featherman and Pavlou (2003). This instrument assesses concerns about potential negative consequences of AI adoption, including: "using AI tools might compromise student data privacy", and "I worry that AI could make errors that mislead students". Negative items were reverse coded appropriately. Cronbach's α = .88.

Demographic and Control Variables

We recorded gender (male/female), year of study (1-4), and prior AI training (yes/no). These variables served as controls in the regression and mediation models; gender and year of study were also used in subgroup comparisons.

Procedure

Data were collected during the first and second semesters of 2025. Participants were recruited through announcements in required mathematics education courses and email invitations distributed by program coordinators. The online survey took approximately 20-25 minutes. Participants were informed that participation was voluntary, their responses would remain confidential and be used only for research, and they could withdraw at any time. They completed an informed consent form before the questionnaire. To reduce response bias, items within each construct were randomized, and attention-check items were included (e.g., "Please select 'agree' for this item"). Responses failing more than one attention check were excluded. The survey platform was configured to accept one response per IP address. Responses completed in fewer than eight minutes were reviewed as potentially careless. Of 142 initial responses, 12 were excluded because of incomplete data (n = 8), failed attention checks (n = 3), or implausibly short completion times (n = 1), yielding a final sample of 130.

Data Analysis

The data were analyzed in multiple phases to address the five RQs. Analyses were conducted using IBM SPSS statistics (version 28) and R (version 4.3.1) with the lavaan, mediation, car, interactions, and lm.beta packages.

Preliminary Analyses

Preliminary analyses screened for missing values, outliers, and violations of assumptions. Missing data were < 3% across all variables and were handled using listwise deletion given the low missingness rate. The missing completely at random (MCAR) pattern was confirmed by Little's MCAR test ($\chi^2 = 45.32$, $p = .412$). Univariate outliers were identified using standardized scores ($|z| > 3.29$); no extreme outliers required removal. Multivariate outliers were assessed via Mahalanobis distance ($p < .001$); two cases exceeded the criterion but were retained after examination revealed plausible response patterns. Assumptions for parametric analyses were evaluated: normality was assessed through Shapiro-Wilk tests, skewness, and kurtosis (all within acceptable ranges); homoscedasticity was examined via Levene's test and residual plots; multicollinearity was evaluated using variance inflation factors (VIF) (< 3.0 for all predictors, well below the threshold of 10); and linearity was confirmed through scatterplot inspection.

Primary Analyses by Research Question

Hierarchical multiple regression tested the incremental predictive power of TAM constructs and AI-specific constructs beyond demographic variables (**RQ1**). Three models were estimated: model 1 included only demographic controls (gender, year of study, prior AI training); model 2 added TAM constructs (PU and PEOU); model 3 added extended constructs (AI awareness, trust in AI, and perceived risk). Standardized coefficients (β), R^2 change, and F-change statistics were evaluated. Three separate mediation models tested trust as a mediator of the relationships of

(a) AI awareness,

(b) PEOU, and

(c) PU with adoption intention (**RQ2**).

Mediation analyses employed Hayes' (2018) PROCESS methodology with bias-corrected bootstrap confidence intervals (CIs) (1,000 resamples, 95% CI). Indirect effects, direct effects (c'), and proportion mediated were computed. Moderation analyses tested whether perceived risk moderated the relationships of

(a) PU,

(b) trust in AI, and

(c) AI awareness with adoption intention (**RQ3**).

Predictors and moderators were mean-centered prior to computing interaction terms. Simple slopes were probed at low ($-1SD$), mean, and high ($+1SD$) levels of perceived risk using the interactions package.

Standardized regression coefficients from the full model (model 3) were compared across the total sample and demographic subgroups (gender, year level) (**RQ4**). Subgroup-specific regression models evaluated whether predictor importance varied across male and female participants and lower-year (years 1-2) vs. upper-year (years 3-4) students. SEM using lavaan tested the theoretically derived sequential pathway: AI awareness → perceived ease → PU → trust → adoption intention (RQ5). Bootstrap standard errors (500 resamples) provided CIs for indirect effects. Model fit was evaluated using multiple indices: Chi-square test, comparative fit index (CFI) (> .95), Tucker-Lewis index (TLI) (> .95), root mean square error of approximation (RMSEA) (< .08), and standardized root mean square residual (SRMR) (< .08). An alternative model with reversed ordering (trust preceding TAM constructs) was tested for comparison using AIC and BIC criteria. All significance tests employed $\alpha = .05$. For multiple comparisons within RQs, false discovery rate (FDR) correction using the Benjamini-Hochberg procedure was applied. We reported the effect sizes in line with Cohen's (1988) guidelines: R^2 for variance explained, Cohen's f^2 for regression effects, and κ^2 (kappa-squared) for mediation effect sizes.

Table 1. Descriptive statistics for study variables (N = 130)

Variable	M	SD	MN	MX	Skewness	Kurtosis
AI awareness	3.19	0.82	0.90	4.99	−0.04	−0.38
PEOU	3.41	0.75	1.64	5.59	0.11	0.12
PU	3.56	0.83	1.64	5.49	−0.10	−0.41
Trust in AI	3.17	0.91	0.87	5.31	−0.10	−0.20
Adoption intention	3.34	0.86	0.76	5.88	0.13	0.24
Perceived risk	2.84	0.91	0.70	6.21	0.12	0.35

Note. MN: Minimum & MX: Maximum

RESULT

This study investigated an expanded TAM that included AI awareness, trust in AI, and perceived risk alongside conventional TAM constructs. The extended model was used to predict preservice mathematics teachers' intentions to adopt AI-driven objects-to-think-with. The analysis was guided by five RQs and used hierarchical multiple regression, mediation, moderation, relative importance analysis, and SEM.

Preliminary Analyses and Descriptive Statistics

Table 1 presents descriptive statistics for all continuous variables. Mean scores on the five-point Likert scales indicated moderate-to-positive views of all constructs. Adoption intention (M = 3.34, SD = 0.86) reflected moderate readiness to use AI tools in future teaching. PU had the highest mean (M = 3.56, SD = 0.83), suggesting that participants viewed AI-driven objects-to-think-with as valuable in the classroom. Trust in AI (M = 3.17, SD = 0.91) and AI awareness (M = 3.19, SD = 0.82) were moderate, whereas perceived risk was lower (M = 2.84, SD = 0.91), indicating comparatively limited concern about AI deployment. All variables had acceptable skewness (<|1.0|) and kurtosis (<|2.0|), supporting the assumptions for parametric analyses.

Bivariate correlations (**Table 2**) revealed that adoption intention correlated positively with PU (r = .64, $p < .001$), trust ($r = .68$, $p < .001$), perceived ease ($r = .58$, $p < .001$), and AI awareness ($r = .55$, $p < .001$), while correlating negatively with perceived risk (r = −.42, $p < .001$). These moderate to strong correlations

Table 2. Correlation matrix for study variables

Variable	1	2	3	4	5	6
1. AI awareness	-					
2. PU	.45***	-				
3. POEU	.52***	.62***	-			
4. Trust in AI	.48***	.40***	.50***	-		
5. Adoption intention	.55***	.58***	.64***	.68***	-	
6. Perceived risk	−.38 ***	−.32 ***	−.40 ***	−.35 ***	−.42 ***	-

Note. ***$p < .001$

Table 3. Hierarchical regression model comparison for adoption intention

Model	R^2	Adjusted R^2	ΔR^2	F
Model 1: Demographics	.031	.008	–	1.34
Model 2: + TAM constructs	.504	.484	.474***	25.25***
Model 3: + Extended constructs	.623	.598	.118***	24.97***

Note. ***$p < .001$

Table 4. Final regression model coefficients predicting adoption intention

Predictor	B	Standard error	β	t	p	95% CI
Intercept	0.42	0.36	-	1.17	.245	[−0.29, 1.13]
Gender (male)	0.02	0.11	0.01	0.19	.852	[−0.19, 0.23]
Year	0.03	0.04	0.05	0.79	.432	[−0.04, 0.10]
Prior training (yes)	0.08	0.11	0.05	0.77	.443	[−0.13, 0.29]
PU	0.27	0.09	0.26	3.01	.003**	[0.09, 0.45]
PEOU	0.13	0.10	0.11	1.33	.187	[−0.06, 0.32]
AI awareness	0.20	0.08	0.19	2.49	.014*	[0.04, 0.36]
Trust in AI	0.36	0.08	0.38	4.73	< .001***	[0.21, 0.51]
Perceived risk	−0.15	0.06	−0.16	−2.34	.021*	[−0.27, −0.02]

Note: *$p < .05$; **$p < .01$; ***$p < .001$; Model $R^2 = .623$; Adjusted $R^2 = .598$; $F(8, 121) = 24.97$; & $p < .001$

show that both traditional TAM and extended notions are still useful. The multicollinearity diagnostics showed that the VIF <3.0 for all variables were acceptable. This meant that multicollinearity did not pose a threat to the regression analysis.

Direct Predictors of Adoption Intention

RQ1 examined whether PU, PEOU, AI awareness, trust in AI, and perceived risk significantly predicted adoption intention. Hierarchical multiple regression tested three models:

(1) demographics only (gender, year of study, prior AI training);

(2) demographics plus conventional TAM constructs (PU and PEOU); and

(3) demographics, TAM constructs, and extended constructs (AI awareness, trust in AI, and perceived risk).

Table 3 shows that the model comparison results were statistically significant in incremental explanatory power at each step. Model 1 (demographics) explained minimal variance, $R^2 = .031$, $F(3,126) = 1.34$, $p = .264$. This result indicates that demographic characteristics alone poorly predicted adoption intentions. We added TAM constructs in model 2 which then produced substantial improvement, $\Delta R^2 = .474$, $F_{\text{change}}(2,124) = 58.91$, $p < .001$, with total variance explained increasing to $R^2 = .504$. Model 3 tested the full extended TAM. This yielded further significant improvement, $\Delta R^2 = .118$, $F_{\text{change}}(3,121) = 12.63$, $p < .001$, with final $R^2 = .623$, adjusted $R^2 = .598$. These results show that AI-specific constructs add substantial predictive value beyond traditional TAM.

Parameter estimates for the final model (**Table 4**) revealed that trust in AI emerged as the strongest predictor ($\beta = .38$, $p < .001$), followed by PU ($\beta = .26$, $p = .003$) and AI awareness ($\beta = .19$, $p = .014$). After controlling other factors, PEOU did not significantly predict adoption intention (β=.11, p=.187). This suggests that its effect operates indirectly, particularly through PU. However, our results found perceived risk to have a significant negative relationship with adoption intention (β = -0.16, p = 0.021). These findings address **RQ1**: PU, trust in AI, AI awareness, and perceived risk were significant predictors, whereas PEOU was not significant in the comprehensive model.

Trust as Mediator

To answer **RQ2**, we examined whether trust in AI mediated the relationships of

(a) AI awareness,

(b) PEOU, and

(c) PU with adoption intention.

Table 5. Mediation analysis: Trust as mediator

Pathway	a	p_a	b	p_b	Indirect	95% CI	Proportion mediated
Awareness → trust → intention	0.54	< .001	0.58	< .001	0.31	[0.19, 0.45]	.585
Ease → trust → intention	0.49	< .001	0.61	< .001	0.30	[0.17, 0.44]	.468
Usefulness → trust → intention	0.55	< .001	0.57	< .001	0.31	[0.20, 0.44]	.442

Note: a: Predictor → mediator; b: Mediator → outcome; Indirect effects tested with 1,000 bootstrap resamples; & CI: Bias-corrected 95% CI

Table 6. Moderation analysis: Perceived risk as moderator

Interaction model	Main X	p	Main risk	p	Interaction	p
Usefulness × risk	0.34	<.001	−0.19	.002	−0.18	.009**
Trust × risk	0.37	<.001	−0.17	.006	−0.21	.004**
Awareness × risk	0.29	.001	−0.20	.001	−0.14	.048*

Note: *p < .05; **p < .01; ***p < .001; & All predictors mean-centered

Table 7. Simple slopes analysis for moderation effects

Model	Risk level	Slope	Standard error	t	p
Usefulness × risk	Low ($-1SD$)	0.52	0.09	5.66	< .001
	Mean	0.34	0.06	5.36	< .001
	High ($+1SD$)	0.16	0.08	2.01	.047
Trust × risk	Low ($-1SD$)	0.58	0.10	5.97	< .001
	Mean	0.37	0.07	5.58	< .001
	High ($+1SD$)	0.16	0.08	2.09	.039
Awareness × risk	Low ($-1SD$)	0.43	0.09	4.62	< .001
	Mean	0.29	0.07	4.36	< .001
	High ($+1SD$)	0.15	0.09	1.71	.089

Mediation analyses utilized bias-corrected bootstrap CIs (1,000 resamples) in accordance with Hayes' (2018) PROCESS approach. The results in **Table 5** showed significant indirect effects via trust for all three pathways, addressing all three components of **RQ2**. For the awareness pathway (**RQ2a**), AI awareness positively predicted trust ($a = 0.54$, $p < .001$), which in turn predicted adoption intention ($b = 0.58$, $p < .001$). The indirect effect was significant (indirect = 0.31, 95% CI [0.19, 0.45]), accounting for 58.5% of the total effect (proportion mediated = 0.585). This indicates substantial partial mediation. The direct effect remained significant (c^′=0.22, p=.012), confirming partial mediation.

For the perceived ease pathway (**RQ2b**), ease predicted trust ($a = 0.49$, $p < .001$), and trust predicted intention controlling for ease ($b = 0.61$, $p < .001$). The indirect effect was significant (indirect = 0.30, 95% CI [0.17, 0.44]), with proportion mediated = 0.468 (46.8%). However, the direct effect of ease on intention remained marginally significant ($c' = 0.34$, $p = .042$), supporting partial mediation. For the PU pathway (**RQ2c**), usefulness predicted trust ($a = 0.55$, $p < .001$), and trust predicted intention ($b = 0.57$, $p < .001$). The indirect effect was significant (indirect = 0.31, 95% CI [0.20, 0.44]), with proportion mediated = 0.442 (44.2%). Usefulness also maintained a significant direct effect (c^′=0.39, p=.001). This further supports partial rather than complete mediation.

These results reveal a consistent pattern: trust functioned as a significant but incomplete mediator, accounting for 44.2%-58.5% of the total effects of the cognitive predictors on adoption intention. The remaining direct effects indicate that awareness, ease of use, and usefulness also influence intention through mechanisms other than trust.

Moderation by Perceived Risk

To answer **RQ3**, we tested whether perceived risk moderated relationships between

(a) PU and adoption intention,

(b) trust and adoption intention, and

(c) AI awareness and adoption intention.

Moderation analyses employed mean-centered predictors with interaction terms. The results in **Table 6** showed a significant interaction between all three models, addressing all three components of **RQ3**. The usefulness × risk interaction was significant ($B = -0.18$, $p = .009$), with the interaction term explaining an additional 3.2% of variance beyond main effects ($\Delta R^2 = .032$).

Simple slopes analysis (**Table 7**) revealed that PU strongly predicted intention at low risk ($-1SD$: $b = 0.52$, $p < .001$), moderately at mean risk ($b = 0.34$, $p < .001$), but showed attenuated effects at high risk ($+1SD$: $b = 0.16$, $p = .047$). This represents a 69% reduction in effect size from low to high risk. The trust × risk interaction was similarly significant ($B = -0.21$, $p = .004$), explaining an additional 3.7% variance ($\Delta R^2 = .037$). Simple slopes showed trust effects diminished from $b = 0.58$ ($p < .001$) at low risk to $b = 0.16$ ($p = .039$) at high risk—a 72% reduction. The awareness × risk interaction

Table 8. Relative importance of predictors across subgroups (standardized coefficients)

Predictor	Overall	Male	Female	Years 1-2	Years 3-4
PU	.26**	.41***	.19*	.19*	.34**
PEOU	.11	.08	.13	.21*	.05
AI awareness	.19*	.16	.21*	.18	.19*
Trust	.38***	.28**	.44***	.32**	.42***
Perceived risk	−.16 *	−.08	−.22 **	−.14	−.18 *

Note: *p < .05; **p < .01; & ***p < .001

Table 9. Model R^2 by subgroup

Subgroup	N	R^2
Overall sample	130	.623
Male	46	.591
Female	84	.637
Years 1-2	70	.524
Years 3-4	60	.648

was marginally significant ($B = -0.14$, $p = .048$), with 2.4% additional variance explained ($\Delta R^2 = .024$). Awareness effects decreased from $b = 0.43$ ($p < .001$) at low risk to $b = 0.15$ ($p = .089$, non-significant) at high risk.

These interaction patterns show that perceived risk significantly weakened the positive influence of cognitive and affective predictors on adoption intention. Even when teachers perceived AI tools as valuable and trustworthy and understood what AI could do, high perceived risk weakened these positive appraisals. These results address **RQ3** and confirm perceived risk as a substantial barrier to adoption.

Relative Importance Across Subgroups

To address **RQ4**, we analyzed the comparative significance of TAM and AI-specific variables among various demographic groupings. We examined standardized regression coefficients and R² values for the whole sample, as well as for groups based on gender and year level. Overall model results (**Table 8**) revealed that trust demonstrated the highest standardized coefficient ($\beta = .38$), followed by PU ($\beta = .26$), AI awareness ($\beta = .19$), perceived risk ($\beta = -.16$), and perceived ease ($\beta = .11$, non-significant). We then compared the collective contribution of AI-specific constructs (awareness, trust, risk) to traditional TAM constructs (usefulness, ease). Hierarchical regression indicated AI-specific constructs explained 11.8% incremental variance beyond TAM constructs, indicating that AI-specific constructs added meaningful explanatory value beyond TAM constructs.

Subgroup analyses revealed notable gender differences. For male preservice teachers ($n = 46$), PU was the strongest predictor ($\beta = .41$), whereas for female preservice teachers ($n = 84$), trust was most important ($\beta = .44$). Risk perception showed stronger negative effects for females ($\beta = -.22$) compared to males ($\beta = -.08$), indicating greater risk sensitivity among female participants. Year-level comparisons (years 1-2 vs. 3-4)

Table 10. SEM fit indices

Fit index	Value
χ^2	8.32
df	4
p-value	.081
CFI	0.984
TLI	0.961
RMSEA	0.091
RMSEA 90% CI	[0.000, 0.173]
SRMR	0.032
AIC	1,124.5
BIC	1,187.3

showed that upper-year students demonstrated higher importance for PU ($\beta = .34$) relative to lower-year students ($\beta = .19$), indicating stronger usefulness effects among upper-year students.

Model R^2 varied across subgroups (**Table 9**), with the full sample model explaining 62.3% of variance. Gender-specific models explained comparable variance (males: 59.1%; females: 63.7%), while year-level models showed lower explanatory power for lower-year students (52.4%) compared to upper-year students (64.8%), suggesting the model functions more strongly for advanced preservice teachers with greater pedagogical knowledge.

Sequential Mediation Pathway Testing

RQ5 tested a theoretically derived sequential mediation pathway: AI awareness → perceived ease → PU → trust → adoption intention. SEM with bootstrapped standard errors (500 resamples) was employed.

The proposed sequential model demonstrated acceptable-to-good fit (**Table 10**): $\chi^2(4) = 8.32$, $p = .081$; CFI = 0.984; TLI = 0.961; RMSEA = 0.091 [90% CI: 0.000, 0.173]; SRMR = 0.032. Path coefficients (**Table 11**) revealed significant effects at each stage. AI awareness significantly predicted perceived ease ($a_1 = 0.41$, $p < .001$), which predicted PU ($d_{21} = 0.57$, $p < .001$), which in turn predicted trust ($d_{31} = 0.34$, $p = .001$). Trust strongly predicted adoption intention ($b_1 = 0.53$, $p < .001$). The full sequential indirect effect (awareness → ease → usefulness → trust → intention) was significant (indirect = 0.031, 95% CI [0.009, 0.061]), though smaller in magnitude than simpler pathways due to the multiplicative nature of serial mediation.

Table 11. Sequential mediation path coefficients

	Path	Estimate	Standard error	z	p
Direct paths	Awareness → ease	0.41	0.080	5.01	< .001
	Ease → usefulness	0.57	0.090	6.51	< .001
	Usefulness → trust	0.34	0.100	3.31	.001
	Trust → intention	0.53	0.080	6.40	< .001
	Awareness → intention (direct)	0.19	0.080	2.42	.016
Indirect effects	Full sequential (awareness → ease → use → trust → intention)	0.031	0.013	-	-
	Awareness → ease → use → intention	0.069	0.022	-	-
	Awareness → ease → intention	0.042	0.020	-	-
	Total indirect effect	0.142	0.034	-	-

Note. 95% CIs: Full sequential [0.009, 0.061]; Ease→use→intention [0.032, 0.118]; Ease→intention [0.009, 0.088]; Total [0.082, 0.213]; & Bootstrap: 500 resamples

Additional indirect pathways were tested: awareness → ease → usefulness → intention (indirect = 0.069, 95% CI [0.032, 0.118]) and awareness → ease → intention (indirect = 0.042, 95% CI [0.009, 0.088]). The total indirect effect through all pathways was 0.142 (95% CI [0.082, 0.213]), accounting for 37.6% of the total effect of awareness on intention.

Model comparison against an alternative model (awareness → trust → ease → usefulness → intention) favored the proposed model. The alternative model fit more poorly (ΔAIC = 12.4; ΔBIC = 9.7), with lower CFI (0.968 vs. 0.984) and higher RMSEA (0.112 vs. 0.091). These findings validate the theoretical proposition that perceived ease precedes PU (consistent with TAM), and both cognitive appraisals preceded trust formation, which directly influences behavioral intentions.

DISCUSSION

This study examined an extended TAM that integrated AI-specific constructs—AI awareness, trust in AI, and perceived risk—alongside traditional TAM variables to predict preservice mathematics teachers' intentions to adopt AI-driven learning objects. The findings provide compelling evidence for the superiority of this extended model and offer important theoretical and practical contributions to understanding AI adoption in teacher education.

Theoretical Contributions and Literature Alignment

The extended TAM model explained 62.3% of the variance in adoption intention, exceeding the 35%-50% typically reported in recent studies of educational technology adoption (Al-Rahmi et al., 2019; Huang et al., 2020). This improvement plausibly reflects the inclusion of AI-specific constructs that prior research has recognized as important but has rarely been examined within a cohesive TAM framework. Nazaretsky et al. (2022) established that cultivating trust is essential to educators' acceptance of AI-driven objects-to-think-with. Consistent with this work, trust was the strongest direct predictor of adoption intention (β = .38) and mediated 44.2%-58.5% of the effects of awareness, ease of use, and usefulness on intention.

Prior studies show that PU and PEOU predict technology acceptance across contexts (Davis, 1989; Scherer et al., 2021; Venkatesh & Davis, 2000). However, TAM explains less when context-specific factors are omitted (Celik et al., 2022; Tondeur et al., 2019). Our findings reinforce this limitation: PU remained significant (β = .26), whereas PEOU was not significant in the comprehensive model (β = .11, p = .187), suggesting that ease operates primarily through other variables. This pattern is consistent with research showing that ethically consequential technologies such as AI require attention to factors beyond usability, including trust and perceived risk (Kajiwara et al., 2023).

Addressing Critical Gaps in the Literature

Despite growing interest in AI in education, key gaps remain. First, risk perception is rarely integrated into adoption models. While Akgun and Greenhow (2022) and Khosravi et al. (2022) highlight ethical and explainability concerns, few studies examine perceived risk as a moderator. Our findings address this by showing that risk significantly weakens the effects of usefulness, trust, and awareness on adoption intentions. Secondly, research has focused largely on in-service teachers, with limited attention to preservice populations (Chounta et al., 2022; Kim & Kim, 2022). Our results show that adoption predictors vary by developmental stage and gender, with upper-year students emphasizing usefulness (β = .34 vs. .19) and females showing greater risk sensitivity, consistent with TPACK perspectives (Valtonen et al., 2020). Also, few studies test mediation or sequential pathways. Although AI awareness is recognized as foundational (Ng et al., 2021; Southworth et al., 2023), empirical validation is scarce. Our findings support a sequential pathway (awareness → ease → usefulness → trust → intention), where trust acts as a proximal driver, and the model outperforms alternative structures (ΔAIC = 12.4).

Major Contributions of the Current Study

This study advances the literature in four keyways. First, it provides empirical evidence for an extended TAM integrating cognitive (awareness, ease of use, usefulness), affective (trust), and barrier (risk) constructs within a unified framework. Unlike prior studies that examined these factors separately (Akgun & Greenhow, 2022; Nazaretsky et al., 2022), our findings show that trust plays a central role in translating cognitive evaluations into behavioral intention. Perceived risk significantly weakens these relationships, addressing concerns raised by Khosravi et al. (2022). Secondly, the study strengthens methodological rigor by combining hierarchical regression, mediation, moderation, and SEM. FDR correction and bootstrapping address limitations noted in prior work (Kajiwara et al., 2023). Thirdly, it addresses a disciplinary gap by focusing on preservice mathematics teachers, a group underrepresented in AI research (Hwang & Tu, 2021). Finally, these findings indicate that trust and pedagogical usefulness, rather than ease of use, are key drivers of adoption. This suggests that professional development should prioritize trustworthy and pedagogically sound AI applications over purely technical training.

Practical Implications

These findings have immediate implications for teacher education programs preparing preservice teachers for AI-enhanced instruction. Programs should

(1) build calibrated trust through transparent and understandable AI demonstrations;

(2) address privacy, algorithmic bias, and error management directly;

(3) tailor support to gender and year of study where subgroup evidence indicates different needs; and

(4) integrate AI awareness into pedagogy courses, linking technical knowledge to demonstrable teaching value.

Limitations

The following are some of the identifiable limitations of this study:

1. This study used a cross-sectional survey design, which limits causal inference because the observed associations reflect a single time point rather than temporal change.
2. Data were collected at one South African university, which may limit the generalizability of the findings to other institutional contexts, teacher education programs, countries, or technological infrastructures.
3. Even though we randomized the items and added attention checks, using self-report measures can still lead to social desirability and common-method bias.
4. Additionally, AI awareness and perceived risk were assessed by self-reported perceptions rather than objective evaluations of competence or exposure to AI technologies. This may have influenced the accuracy of the findings.

CONCLUSIONS

This study identified factors shaping preservice mathematics teachers' intentions to adopt AI-driven objects-to-think-with. Extending TAM with AI awareness, trust, and perceived risk showed that trust and PU were the strongest predictors, whereas ease of use operated indirectly. Awareness strengthened usefulness and trust, while perceived risk reduced intention and weakened the positive effects of usefulness, trust, and awareness. Accordingly, integrating AI technologies into teacher education is insufficient without calibrated trust, clear pedagogical value, and structured preparation that addresses privacy, reliability, bias, and ethical risks. The findings support systematic, evidence-informed AI integration in mathematics teacher education.

Recommendations

Based on the results of this study, we made the following recommendations:

1. Universities and teacher education programs should integrate structured AI preparation into curricula so that preservice teachers can understand, use, and evaluate AI-driven objects-to-think-with for mathematics teaching and cognitive engagement.
2. Teacher education programs should build calibrated trust by demonstrating AI systems' reliability, transparency, fairness, and limitations.
3. Teacher education programs should provide supervised, hands-on activities that allow preservice teachers to evaluate and use AI tools in authentic classroom scenarios.
4. Institutions should implement policies and training that protect privacy, address ethical and bias-related concerns, and support safe and responsible AI use.

Recommendations for Future Research

In view of the study's limitations and findings, future research should follow the following directions:

1. Future studies should use longitudinal, multi-wave, or experimental designs to test the temporal ordering and causal direction of awareness, ease of use, usefulness, trust, perceived risk, and adoption intention.
2. Researchers should replicate and validate the model with larger, multi-institutional, and cross-national samples, including measurement invariance tests across institutional and sociocultural contexts.

3. Future work should combine self-report measures with objective assessments of AI literacy, performance-based tasks, actual-use or log data, and classroom observations to reduce common-method bias and distinguish intention from enacted adoption.
4. Intervention studies should compare alternative forms of AI literacy training, trust calibration, and risk-mitigation support, while examining whether effects differ by gender, year of study, prior AI training, and access to digital resources.

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REFERENCES

Acquah, B. Y. S., Arthur, F., Salifu, I., Quayson, E., & Nortey, S. A. (2024). Preservice teachers' behavioural intention to use artificial intelligence in lesson planning: A dual-staged PLS-SEM-ANN approach. *Computers and Education: Artificial Intelligence*, *7*, Article 100307. https://doi.org/10.1016/j.caeai.2024.100307

Akgun, S., & Greenhow, C. (2022). Artificial intelligence in education: Addressing ethical challenges in K-12 settings. *AI and Ethics*, *2*(3), 431-440. https://doi.org/10.1007/s43681-021-00096-7

Alejandro, I. M. V., Sanchez, J. M. P., Sumalinog, G. G., Mananay, J. A., Goles, C. E., & Fernandez, C. B. (2024). Pre-service teachers' technology acceptance of artificial intelligence (AI) applications in education. *STEM Education*, *4*(4), 445-465. https://doi.org/10.3934/steme.2024024

Alissa, R. A. S., & Hamadneh, M. A. (2023). The level of science and mathematics teachers' employment of artificial intelligence applications in the educational process. *International Journal of Education in Mathematics, Science and Technology*, *11*(6), 1597-1608. https://doi.org/10.46328/ijemst.3806

Al-Rahmi, W. M., Yahaya, N., Aldraiweesh, A. A., Alamri, M. M., Aljarboa, N. A., Alturki, U., & Aljeraiwi, A. A. (2019). Integrating technology acceptance model with innovation diffusion theory: An empirical investigation on students' intention to use e-learning systems. *IEEE Access*, *7*, 26797-26809. https://doi.org/10.1109/ACCESS.2019.2899368

Antonietti, C., Cattaneo, A., & Amenduni, F. (2022). Can teachers' digital competence influence technology acceptance in vocational education? *Computers in Human Behavior*, *132*, Article 107266. https://doi.org/10.1016/j.chb.2022.107266

Celik, I., Dindar, M., Muukkonen, H., & Järvelä, S. (2022). The promises and challenges of artificial intelligence for teachers: A systematic review of research. *TechTrends*, *66*(4), 616-630. https://doi.org/10.1007/s11528-022-00715-y

Chounta, I. A., Bardone, E., Raudsep, A., & Pedaste, M. (2022). Exploring teachers' perceptions of Artificial Intelligence as a tool to support their practice in Estonian K-12 education. *International Journal of Artificial Intelligence in Education*, *32*(3), 725-755. https://doi.org/10.1007/s40593-021-00243-5

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Cui, Y. L., Zeng, M. L., Du, X. K., & He, W. M. (2025). What shapes learners' trust in AI? A meta-analytic review of its antecedents and consequences. *IEEE Access*, *13*, 164008-164025. https://doi.org/10.1109/ACCESS.2025.3611367

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340. https://doi.org/10.2307/249008

Dindar, M., Suorsa, A., Hermes, J., Karppinen, P., & Näykki, P. (2021). Comparing technology acceptance of K-12 teachers with and without prior experience of learning management systems: A COVID-19 pandemic study. *Journal of Computer Assisted Learning, 37*(6), 1553-1565. https://doi.org/10.1111/jcal.12552

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies, 59*(4), 451-474. https://doi.org/10.1016/S1071-5819(03)00111-3

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51-90. https://doi.org/10.2307/30036519

Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (2nd ed.). Guilford Press.

Huang, F., Teo, T., & Zhou, M. (2020). Chinese students' intentions to use the Internet-based technology for learning. *Educational Technology Research and Development, 68*(1), 575-591. https://doi.org/10.1007/s11423-019-09695-y

Hwang, G. J., & Tu, Y. F. (2021). Roles and research trends of artificial intelligence in mathematics education: A bibliometric mapping analysis and systematic review. *Mathematics, 9*(6), Article 584. https://doi.org/10.3390/math9060584

Kajiwara, Y., Matsuoka, A., & Shinbo, F. (2023). Machine learning role playing game: Instructional design of AI education for age-appropriate in K-12 and beyond. *Computers and Education: Artificial Intelligence, 5*, Article 100162. https://doi.org/10.1016/j.caeai.2023.100162

Kelly, S., Kaye, S. A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics, 77*, Article 101925. https://doi.org/10.1016/j.tele.2022.101925

Khosravi, H., Shum, S. B., Chen, G., Conati, C., Tsai, Y. S., Kay, J., Knight, S., Martinez-Maldonado, R., Sadiq, S., & Gašević, D. (2022). Explainable artificial intelligence in education. *Computers and Education: Artificial Intelligence, 3*, Article 100074. https://doi.org/10.1016/j.caeai.2022.100074

Kim, N. J., & Kim, M. K. (2022). Teacher's perceptions of using an artificial intelligence-based educational tool for scientific writing. *Frontiers in Education, 7*. https://doi.org/10.3389/feduc.2022.755914

Kuzu, S. (2025). Artificial intelligence in pre service teacher education: Bibliometrics analysis. *Pedagogical Research, 10*(4), Article em0249. https://doi.org/10.29333/pr/17402

Laru, J., Celik, I., Jokela, I., & Mäkitalo, K. (2025). The antecedents of pre-service teachers' AI literacy: perceptions about own AI driven applications, attitude towards AI and knowledge in machine learning. *European Journal of Teacher Education, 48*(5), 964-986. https://doi.org/10.1080/02619768.2025.2535623

Lin, Y., & Yu, Z. (2023). Extending technology acceptance model to higher-education students' use of digital academic reading tools on computers. *International Journal of Educational Technology in Higher Education, 20*, Article 34. https://doi.org/10.1186/s41239-023-00403-8

Liu, N. (2025). Exploring the factors influencing the adoption of artificial intelligence technology by university teachers: The mediating role of confidence and AI readiness. *BMC Psychology, 13*, 311. https://doi.org/10.1186/s40359-025-02620-4

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research, 13*(3), 334-359. https://doi.org/10.1287/isre.13.3.334.81

Milicevic, N., Kalas, B., Djokic, N., Malcic, B., & Djokic, I. (2024). Students' intention toward artificial intelligence in the context of digital transformation. *Sustainability, 16*(9), Article 3554. https://doi.org/10.3390/su16093554

Mosia, M., & Matabane, M. E. (2022). Exploring factors that serve as predictors for mathematics and sciences pre-service teachers to use ICT in teaching. *Research in Educational Policy and Management, 4*(1), 80-91. https://doi.org/10.46303/repam.2022.10

Mosia, M., & Nannim, F. A. (2026). Heterogeneous self-efficacy effects in mathematics pre-service teachers' AI adoption: A Bayesian moderated mediation analysis. *Frontiers in Education, 11*. https://doi.org/10.3389/feduc.2026.1803423

Mosia, M., Nannim, F. A., & Egara, F. O. (2026). AI literacy-related domains and AI-TPACK readiness among preservice mathematics teachers: A factor-informed structural equation modelling study. *Computers and Education: Artificial Intelligence, 11*, Article 100650. https://doi.org/10.1016/j.caeai.2026.100650

Nazaretsky, T., Ariely, M., Cukurova, M., & Alexandron, G. (2022). Teachers' trust in AI-powered educational technology and a professional development program to improve it. *British Journal of Educational Technology, 53*(4), 914-931. https://doi.org/10.1111/bjet.13232

Nazaretsky, T., Mejia-Domenzain, P., Swamy, V., Frej, J., & Käser, T. (2025). The critical role of trust in adopting AI-powered educational technology for learning: An instrument for measuring student perceptions. *Computers and Education: Artificial Intelligence, 8*, Article 100368. https://doi.org/10.1016/j.caeai.2025.100368

Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence, 2*, Article 100041. https://doi.org/10.1016/j.caeai.2021.100041

Rana, M. M., Siddiqee, M. S., Sakib, M. N., & Ahamed, M. R. (2024). Assessing AI adoption in developing country academia: A trust and privacy-augmented UTAUT framework. *Heliyon, 10*(18), Article e37569. https://doi.org/10.1016/j.heliyon.2024.e37569

Sanusi, I. T., Ayanwale, M. A., & Tolorunleke, A. E. (2024). Investigating pre-service teachers' artificial intelligence perception from the perspective of planned behavior theory. *Computers and Education: Artificial Intelligence, 6*, Article 100202. https://doi.org/10.1016/j.caeai.2024.100202

Scherer, R., Howard, S. K., Tondeur, J., & Siddiq, F. (2021). Profiling teachers' readiness for online teaching and learning in higher education: Who's ready? *Computers in Human Behavior, 118*, Article 106675. https://doi.org/10.1016/j.chb.2020.106675

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education, 128*, 13-35. https://doi.org/10.1016/j.compedu.2018.09.009

Son, T. (2024). Intelligent tutoring systems in mathematics education: A systematic literature review using the substitution, augmentation, modification, redefinition model. *Computers, 13*(10), Article 270. https://doi.org/10.3390/computers13100270

Southworth, J., Migliaccio, K., Glover, J., Reed, D., McCarty, C., Brendemuhl, J., & Thomas, A. (2023). Developing a model for *AI across the curriculum*: Transforming the higher education landscape via innovation in AI literacy. *Computers and Education: Artificial Intelligence, 4*, Article 100127. https://doi.org/10.1016/j.caeai.2023.100127

Tondeur, J., Scherer, R., Baran, E., Siddiq, F., Valtonen, T., & Sointu, E. (2019). Teacher educators as gatekeepers: Preparing the next generation of teachers for technology integration in education. *British Journal of Educational Technology, 50*(3), 1189-1209. https://doi.org/10.1111/bjet.12748

U.S. Department of Education. (2023). Artificial intelligence and the future of teaching and learning: Insights and recommendations. *U.S. Department of Education*. https://www.ed.gov/sites/ed/files/documents/ai-report/ai-report.pdf

Valtonen, T., Leppänen, U., Hyypiä, M., Sointu, E., Smits, A., & Tondeur, J. (2020). Fresh perspectives on TPACK: Pre-service teachers' own appraisal of their challenging and confident TPACK areas. *Education and Information Technologies, 25*(4), 2823-2842. https://doi.org/10.1007/s10639-019-10092-4

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Viberg, O., Cukurova, M., Feldman-Maggor, Y., Alexandron, G., Shirai, S., Kanemune, S., Wasson, B., Tømte, C., Spikol, D., Milrad, M., Coelho, R., & Kizilcec, R. F. (2025). What explains teachers' trust in AI in education across six countries? *International Journal of Artificial Intelligence in Education, 35*(3), 1288-1316. https://doi.org/10.1007/s40593-024-00433-x

Vincent-Lancrin, S., & van der Vlies, R. (2020). *Trustworthy artificial intelligence (AI) in education: Promises and challenges*. OECD Publishing. https://doi.org/10.1787/a6c90fa9-en

Wu, W., Zhang, B., Li, S., & Liu, H. (2022). Exploring factors of the willingness to accept AI-assisted learning environments: An empirical investigation based on the UTAUT model and perceived risk theory. *Frontiers in Psychology, 13*. https://doi.org/10.3389/fpsyg.2022.870777

Zhang, C., Hu, M., Wu, W., Kamran, F., & Wang, X. (2025). Unpacking perceived risks and AI trust influences pre-service teachers' AI acceptance: A structural equation modeling-based multi-group analysis. *Education and Information Technologies, 30*(2), 2645-2672. https://doi.org/10.1007/s10639-024-12905-7