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Modeling the determinants of AI integration in primary mathematics education: A structural equation modeling analysis

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Abstract

This study addresses a critical gap in educational technology research by simultaneously examining the internal and external determinants of Artificial Intelligence (AI) integration in primary mathematics instruction. Using a second-order Structural Equation Modeling (SEM) framework, the study investigates how teachers' attitudes and TPACK competencies (internal factors), alongside policy support, infrastructure, and community engagement (external factors), influence AI utilization among 516 primary school mathematics teachers in Jakarta, Indonesia. The results reveal that internal factors have a strong direct effect on AI utilization ($\beta = 0.791$; $p < 0.001$), while external factors exert a significant indirect influence via internal mediators ($\beta = 0.217$; $p < 0.001$), despite an insignificant direct effect ($\beta = 0.008$; $p = 0.908$). The model explains 78.1% of the variance in AI utilization ($R^2 = 0.781$) and shows high predictive relevance ($Q^2 > 0.70$). These findings underscore the pivotal role of teacher readiness in AI integration, with systemic support enhancing its effectiveness through internal capacity-building. The study contributes an empirically validated instrument and a comprehensive ecological model, offering actionable insights for policymakers and educators in developing nations pursuing ethical, equitable, and sustainable AI integration in primary education.

Keywords: AI integration; educational environment; elementary mathematics; teacher readiness; TPACK

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Introduction

As global education undergoes digital transformation, Artificial Intelligence (AI) is increasingly recognized for reshaping teaching strategies and how students learn (Sanabria-Navarro et al., 2023; Walter, 2024). In Indonesia, this aligns with the 2022–2026 Digital Transformation Strategic Plan, which highlights AI's potential in enhancing primary mathematics education through adaptive tools, real-time insights, and personalized learning support (Olmo-Muñoz et al., 2023; Pineda-Martínez et al., 2023). Tools like intelligent tutoring systems and AI-driven assessments have been linked to improved student engagement and conceptual mastery (Gadanidis, 2017; Hwang & Tu, 2021), while data-informed instruction has been shown to boost both motivation and learning outcomes (Annuš & Kmeť, 2024; Wei et al., 2024). Despite this, research remains concentrated on secondary education in developed nations, with limited focus on AI integration at the primary level in developing countries. This study aims to bridge that gap by exploring how AI can support mathematics learning through the interaction of teacher preparedness and systemic support in Indonesia's educational landscape.

In this study, internal competences refer to teachers' intrinsic capacities encompassing two core constructs: attitudes toward AI and TPACK proficiency (Technological Pedagogical Content Knowledge). The attitudinal component represents teachers' beliefs about AI's utility, ease of use, and ethical implications (El Hajj & Harb, 2023), rooted in the Technology Acceptance Model (TAM). Positive attitudes have been associated with proactive engagement in AI-enabled platforms, such as intelligent tutoring systems and diagnostic learning analytics (S. F. Ng et al., 2021). Meanwhile, TPACK competence, derived from the model by Jia et al. (2022), reflects teachers' ability to integrate content knowledge, pedagogy, and digital technologies effectively. Teachers with high TPACK fluency are more capable of designing meaningful, data-driven instruction using AI-enhanced tools (Rahimi & Kim, 2021; Ye et al., 2024). In this study, internal competence functions not only as a cognitive-affective driver but also as a pedagogical filter that determines the quality and ethics of AI integration.

External competences, in contrast, represent the institutional and ecological capacities that scaffold and sustain AI integration. These include policy-level support, availability of digital infrastructure, and parental or community involvement, as operationalized through the E-TPACK model and Bronfenbrenner's ecological systems theory (Tong & An, 2024). External factors shape the broader ecosystem in which teachers operate; for instance, effective policy mandates, equitable access to digital devices, and culturally informed community engagement can significantly amplify teacher readiness (Azhar et al., 2022; Flores-Vivar & García-Peñalvo, 2023). Conversely, institutional apathy, the digital divide, or AI-related misconceptions within communities can constrain innovation uptake despite high individual capacity (Scherer & Siddiq, 2019). This study postulates that internal competences mediate the relationship between external supports and actual AI utilization, highlighting a reciprocal dependency wherein systemic support enhances teacher capacity, which in turn enables meaningful AI adoption.

Effective integration of Artificial Intelligence (AI) in primary mathematics education demands a conceptual framework that bridges pedagogical, psychological, and systemic dimensions. This study proposes a synthesized model combining TPACK, TAM, and E-TPACK. TPACK (Mishra et al., 2023) underscores the balance of content, pedagogy, and technology as essential teacher competencies, while TAM (Davis & Granić, 2024) highlights perceived usefulness and ease of use as key drivers of technology adoption (Li et al., 2024; Ye et al., 2024). E-TPACK extends this by incorporating Bronfenbrenner's ecological model, emphasizing the role of contextual factors, individual, institutional, and structural, in shaping teacher readiness. Together, these models form a comprehensive framework in which teacher attitudes, TPACK mastery, and systemic support are critical to AI implementation. Teachers with positive perceptions of AI, supported professionally and institutionally, are more likely to apply it effectively in adaptive learning settings (Khong et al., 2023; Ma et al., 2024). Thus, AI integration success hinges not only on individual readiness but also on coherent systemic support within the educational ecosystem.

The rapid integration of Artificial Intelligence (AI) into education underscores an urgent need to examine not only technological preparedness but also the alignment between stakeholder capacities and policy frameworks, particularly in developing countries. While scholarly interest in pedagogical competence and systemic support for AI-based education has grown (El Hajj & Harb, 2023; Jia et al., 2022), there remains a notable scarcity of studies that concurrently investigate both internal (teacher-level) and external (institutional-level) factors, especially within the context of primary education in low- and middle-income countries such as Indonesia. The novelty of this study lies in its ecological-contextual approach, which integrates three theoretical models, TPACK, TAM, and E-TPACK, into a comprehensive framework for examining how teacher readiness and systemic support interactively influence AI adoption in primary mathematics education. This integrative model has rarely been applied with empirical rigor, particularly through second-order reflective–formative modeling using PLS-SEM, as implemented in this research. Existing studies have predominantly concentrated on secondary or higher education in technologically advanced contexts (Li et al., 2024; Tang et al., 2022), leaving a critical gap in understanding AI readiness among primary school teachers in emerging urban environments.

Furthermore, this study introduces an empirically validated diagnostic instrument, the Scale of Mathematics Teachers' Technology Integration (SMTTI), which measures not only teachers' TPACK and attitudes toward AI but also incorporates systemic support components such as educational policy, infrastructure, and community engagement, consistent with Bronfenbrenner's ecological systems theory. This represents a methodological advancement over prior frameworks, which often analyse these variables in isolation. Another key contribution is the study's focus on Jakarta as a representative urban ecosystem within a developing country. This context offers transferable insights for comparable socio-educational settings across Southeast Asia and other similar regions. In contrast to earlier research that tends to underemphasize the role of parents and communities (Khosravi et al., 2023; Scherer & Siddiq, 2019), this study empirically demonstrates the indirect but pivotal influence of these external factors, mediated through internal teacher readiness. Overall, this research addresses both methodological and contextual gaps in the current AI-in-education literature. It offers a practical, evidence-based framework for policymakers and educators, providing actionable insights for designing inclusive and context-sensitive AI integration strategies in primary mathematics instruction. This dual theoretical and applied contribution distinguishes the present study from previous work in the field.

Methods

Research design

This study adopts a second-order SEM within a reflective formative framework to examine how internal and external factors shape AI integration in primary mathematics education. The model captures the complexity of constructs like TPACK and systemic support, while enabling analysis of indirect mediation effects (Hair & Alamer, 2022). Grounded in global literature and tailored to Indonesia's context, where many teachers lack technological pedagogical skills and digital infrastructure remains limited, the study combines TPACK, TAM, and E-TPACK to explain the interplay between teacher readiness and environmental support in fostering effective AI adoption.

Participants

As Indonesia's capital and a prominent urban education hub in Southeast Asia, Jakarta offers a strategic context for investigating readiness and structural barriers to AI integration in primary mathematics instruction. This study surveyed 516 primary mathematics teachers, proportionally sampled across the city's five administrative districts, representing public, faith-based private, and inclusive schools. The sample's diversity ensured representation across socioeconomic and institutional contexts. Predominantly female (80.6%), in line with national and international trends (Reuter et al., 2022), participants mostly taught grades 3 and 5, with 42.6% identifying as senior teachers, educators with strong pedagogical backgrounds but potentially lower openness to technological innovation. This demographic and institutional variation reflects Jakarta's complex educational landscape and strengthens the study's analytical relevance and applicability to other multicultural urban settings in the Global South.

Table 1. Demographic characteristics of research participants

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Female	416	80.6%
	Male	100	19.4%
Teaching Experience	0–5 years	84	16.3%
	6–10 years	128	24.8%
	11–15 years	83	16.1%
	>15 years	220	42.6%
Grade Level Taught	Grade 1	51	9.9%
	Grade 2	87	16.9%
	Grade 3	109	21.1%
	Grade 4	83	16.1%
	Grade 5	102	19.8%

Characteristic	Category	Frequency (n)	Percentage (%)
	Grade 6	84	16.3%
School Type	Public	314	60.9%
	Private	202	39.1%
Administrative Region	Central Jakarta	74	14.3%
	North Jakarta	98	19.0%
	West Jakarta	106	20.5%
	South Jakarta	123	23.8%
	East Jakarta	115	22.3%

Instrument

This study utilized the Scale of Mathematics Teachers' Technology Integration (SMTTI), adapted from Li et al. (2024), to assess primary mathematics teachers' readiness to incorporate Artificial Intelligence (AI) into instruction. Cross-cultural validation involved forward–backward translation, expert evaluation, and a pilot with 35 teachers to ensure linguistic precision and contextual alignment. The instrument is theoretically rooted in TPACK (techno pedagogical knowledge), TAM (attitudinal and behavioural intention), and ecological theory (systemic contextual influences). SMTTI measures two key domains: internal factors (TPACK, TCK/TPK, and AI attitudes) and external factors (policy, infrastructure, parental engagement, sociocultural norms). Data were modelled using a second-order hierarchical structure combining reflective and formative indicators, following Hair and Alamer (2022). Comprising 31 items on a five-point Likert scale, the instrument captures beliefs about AI-enhanced learning tools and contextual supports such as digital literacy and infrastructure availability. Psychometric validation yielded satisfactory results, with factor loadings > 0.70, AVE > 0.50, CR > 0.80, and Cronbach's alpha between 0.82–0.89. Discriminant validity was supported via Fornell–Larcker and HTMT (< 0.90). The online survey format facilitated broad participation while ensuring data integrity through authentication and system safeguards. Overall, SMTTI is a theoretically sound and empirically validated tool for diagnosing teacher preparedness and guiding AI integration strategies in mathematics education.

Model fit and scale validity

Model fit was assessed using second-order reflective–reflective SEM to examine attitudes toward AI, TPACK competence, and external contextual factors in elementary mathematics instruction. The model demonstrated excellent fit ($\chi^2/df = 2.312$, RMSEA = 0.049, SRMR = 0.036, CFI = 0.963, TLI = 0.951), indicating strong structural validity. All constructs showed high internal consistency (CR > 0.94; Cronbach's $\alpha > 0.88$), with convergent validity supported by AVE values > 0.75. Discriminant validity was confirmed via the Fornell–Larcker criterion. These results affirm the model's empirical robustness and theoretical soundness. The web-based SMTTI instrument not only facilitated efficient data distribution but also enabled valid multi-construct measurement in a complex urban context such as Jakarta. Nevertheless, it is important to expand the population scope and account for socio-economic heterogeneity to further enhance external validity. Taken together, the findings affirm that SMTTI is a psychometrically sound and contextually valid tool for assessing teachers' readiness to adopt AI in a systemic and grounded manner.

Table 2. Summary of model fit indices for the SMTTI

Fit Index	Obtained Value	Good Fit Criteria	Acceptable Fit Criteria	Model Fit Assessment
χ^2/df	2.312	< 3	3 – 5	Good fit
RMSEA	0.049	≤ 0.05	0.05 – 0.10	Close fit
SRMR	0.036	≤ 0.05	0.05 – 0.08	Good fit
GFI	0.908	≥ 0.95	0.90 – 0.95	Acceptable fit
AGFI	0.889	≥ 0.90	0.85 – 0.90	Acceptable fit
NFI	0.912	≥ 0.95	0.90 – 0.95	Acceptable fit
CFI	0.963	≥ 0.95	0.90 – 0.95	Excellent fit
TLI	0.951	≥ 0.95	0.90 – 0.95	Excellent fit

Table 3 confirms the strong psychometric properties of the model, with Cronbach's alpha and Composite Reliability values exceeding 0.85, indicating high reliability. Elevated AVE scores, notably for TPCK (0.960) and TCK_TPK (0.857), reflect substantial explanatory power of the latent constructs. Discriminant validity, assessed via the Fornell–Larcker criterion, is evident as the square roots of AVE surpass inter-construct correlations (e.g., √AVE of TPCK = 0.980 > correlation with TCK_TPK = 0.889), affirming construct distinctiveness. These results validate the model's alignment with TPACK and E-TPACK frameworks and support its methodological suitability for application in urban primary education settings, including those with similar contextual features.

Table 3. Reliability and validity

Construct	AVE	CR	Cronbach α	ATT	AIU	CTX	TCKP	TPCK	EDC	PCI
ATT	.763	.941	.921	.874						
AIU	.763	.988	.984	.846	.874					
CTX	.948	.989	.986	.812	.837	.974				
TCKP	.857	.960	.944	.793	.819	.843	.926			
TPCK	.960	.990	.986	.781	.812	.865	.889	.980		
EDC	.989	.997	.996	.759	.798	.888	.916	.941	.995	
PCI	.937	.983	.977	.736	.781	.861	.897	.918	.942	.968

This study adopts a standardized set of abbreviations to represent the key constructs in the research model. ATT (Attitude) captures educators' perceptions of AI integration in teaching, while AIU (AI Utilization) reflects the extent of AI implementation in instructional practice. CTX (Contextual Factors) encompasses external influences such as institutional support and school environments. TCKP merges Technological Content Knowledge (TCK) and Technological Pedagogical Knowledge (TPK), indicating teachers' techno-pedagogical fluency. TPCK denotes Technological Pedagogical Content Knowledge, emphasizing the integrated application of content, pedagogy, and technology. EDC (Educational Challenges) identifies structural and systemic barriers, and PCI (Parental and Community Involvement) measures family and community engagement in supporting AI use in education. These constructs are consistently referenced throughout the empirical analysis, structural model interpretation, and theoretical discussion.

Data collection

Data were collected over three months through an online survey administered to elementary school mathematics teachers across the five administrative regions of Jakarta. This region was selected as the study site because it serves as a national pilot area for the "*Digitalisasi Sekolah*" (School Digitalization) program and demonstrates high levels of ICT device ownership and infrastructure availability. Utilizing a census-based purposive sampling approach, the survey targeted the entire population of active mathematics teachers, distributed officially through the Provincial Education Office. A total of 516 valid responses were obtained, meeting the minimum sample requirement for estimating a second-order SEM model (Hair & Alamer, 2022). The instrument, SMTTI, encompassed constructs such as TPACK, perceived usefulness, perceived ease of use, and attitudes toward AI. It was culturally adapted through a forward-backward translation process and validated by a panel of experts (CVI > 0.85; Cronbach's $\alpha > 0.87$). The survey implementation incorporated token-based access, IP restrictions, and screening questions to ensure data integrity and prevent duplication. Participation was voluntary, anonymous, and conducted following established research ethics protocols. Preliminary data checks revealed no outliers, missing values, or duplicate responses, confirming the dataset's adequacy for analysis using PLS-SEM with SmartPLS 4.0.

Data analysis

Data analysis was conducted using second-order Structural Equation Modelling (SEM) with a reflective–reflective structure and the repeated indicators method, following Hair and Alamer (2022). Due to model complexity and non-normal data distribution, SmartPLS 4.0 was employed as the primary tool, replacing AMOS, in line with Hair and Alamer (2022). Diagnostic tests confirmed violations of normality and homoscedasticity, supporting the appropriateness of the PLS-SEM approach. The analysis comprised two stages: measurement and structural model assessment. All indicators showed strong factor loadings (> 0.70), internal consistency (Cronbach's α and CR > 0.70), and convergent validity (AVE > 0.50), with no multicollinearity issues (VIF < 5). Discriminant validity was confirmed via the Fornell–Larcker criterion.

The structural model demonstrated high explanatory power ($R^2 = 0.781$) and predictive relevance ($Q^2 = 0.744$). Internal factors fully mediated the relationship between external factors and AI utilization ($\beta = 0.217$, $p < 0.001$; VAF = 96.4%), while the direct effect was non-significant. Effect size analysis indicated moderate ($f^2 = 0.145$) to strong ($f^2 = 0.351$) effects. These results highlight the pivotal role of internal readiness, supported by systemic external conditions, in successful AI integration. They also reinforce the theoretical and practical validity of the E-TPACK framework in advancing digital mathematics education in primary schools.

Results

This study's conceptual framework investigates the direct and mediated effects of external factors on AI integration in elementary mathematics education, with internal factors serving as a mediator. Using second-order SEM via SmartPLS 4.0, the model captures the interplay between teacher readiness and systemic support. Internal Factors (IF) comprise Attitude, TPACK, and the combined dimensions of TCK and TPK, while External Factors (EF) include Contextual Factors (CTX), Educational Challenges (EDC), and Parental and Community Involvement (PCI), reflecting the broader ecological and institutional influences on AI adoption in classrooms.

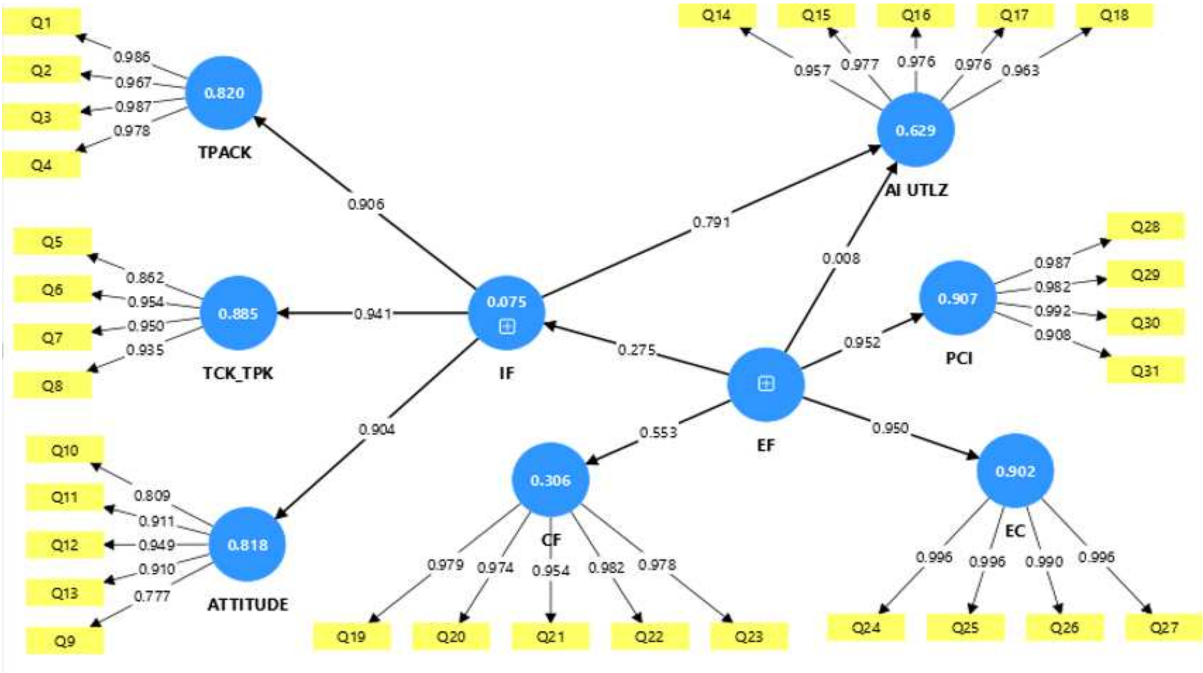

Fig 1. Second-order of SEM

The measurement model was evaluated to ensure construct validity and reliability for Internal Factors (IF), External Factors (EF), and AI Utilization, including analyses of factor loadings, internal consistency, convergent validity, and multicollinearity (Table 4).

Table 4. Measurement model assessment

Construct	Indicators	Indicators	VIF	Cronbach's α	rho_A	CR	AVE
Internal Factors	TPACK	0.957	2.750	0.885	0.885	0.941	0.790
	ATTITUDE	0.977	2.710				
	TCK_TPK	0.976	2.890				
AI Utilization	Q14	0.976	2.280	0.952	0.952	0.963	0.838
	Q15	0.963	2.110				
	Q16	0.906	2.079				
	Q17	0.904	2.069				
	Q18	0.941	3.946				
External Factors	PCI	0.952	2.950	0.902	0.907	0.950	0.902
	EC	0.950	2.870				
	CF	0.553	1.740				

The measurement model shows strong internal consistency for AI Utilization and Internal Factors, with indicator loadings above 0.90. One External Factor indicator (CF) yielded a lower, yet acceptable loading (0.553), suggesting the need for semantic refinement. VIF values under 4 confirm no multicollinearity. Reliability is supported by Cronbach's alpha and CR > 0.88, and AVE > 0.70 confirms convergent validity. Discriminant validity, assessed via the Fornell–Larcker criterion, is met, as AVE square roots exceed inter-construct correlations (see Table 5).

Tabel 5. Discriminant validity

Konstruk	AI Utilization	External Factors	Internal Factors
AI Utilization	0.970		
External Factors	0.225	0.804	
Internal Factors	0.793	0.275	0.846

The measurement model met the required standards for reliability and validity, establishing a sound basis for structural analysis (Table 6). Path analysis revealed a strong direct effect of internal factors, comprising teachers' attitudes and TPACK competence, on AI utilization ($\beta = 0.791$; $T = 16.523$; $p < 0.001$; $f^2 = 0.168$). Although external factors did not exert a significant direct influence ($\beta = 0.008$; $p = 0.908$), their indirect effect through internal mediation was statistically significant ($\beta = 0.217$; $T = 3.872$; $p < 0.001$), confirming a full mediating role. The robust link between external and internal factors ($\beta = 0.275$; $T = 9.706$) highlights the critical role of systemic support in enhancing teacher capacity.

Table 6. Summary of structural path effects and effect sizes

Path	Direct Effect (β)	Indirect Effect (β)	Total Effect (β)	T-value	p-value	f²	Note
External → AI Utilization	0.008	0.217	0.225	3.812	0.000***	0.176	Full mediation via IF
External → Internal Factors (IF)	0.275	–	0.275	9.706	0.000***	9.706	Significant direct impact
Internal Factors → AI Utilization	0.791	–	0.791	16.523	0.000***	0.168	Strongest direct effect

Path analysis revealed that internal factors, specifically teachers' attitudes and TPACK competence, exert a strong and statistically significant direct effect on AI utilization in primary mathematics classrooms ($\beta = 0.791$; $T = 16.523$; $p < 0.001$; $f^2 = 0.168$). In contrast, external factors showed no significant direct influence ($\beta = 0.008$; $p = 0.908$). However, their indirect effect through internal factors was significant ($\beta = 0.217$; $T = 3.872$; $p < 0.001$), confirming a full mediation effect. The notable link between external and internal factors ($\beta = 0.275$; $T = 9.706$) underscores the role of systemic support in enhancing teacher capacity. These findings suggest that successful AI integration should prioritize strengthening teacher readiness, supported by an enabling educational environment. Additional R^2 and Q^2 analyses further validated the model's explanatory and predictive strength (see Table 7).

Table 7. R^2 and Q^2 values for main constructs

Construct	R²	R² Interpretation	Q²	Q² Interpretation
AI Utilization	0.781	Strong	0.744	Highly Relevant (Large)
Internal Factors	0.275	Weak	0.183	Moderately Relevant (Medium)

Table 7 shows that AI utilization has strong explanatory power ($R^2 = 0.781$) and high predictive relevance ($Q^2 = 0.744$), indicating that internal and external factors jointly play a significant role in teachers' AI adoption. In contrast, internal readiness alone has a lower explanatory value ($R^2 = 0.275$), though its predictive relevance remains moderate ($Q^2 = 0.183$). This suggests that external factors alone cannot fully account for internal readiness, highlighting the need for additional mediating variables. The findings affirm the central mediating role of internal factors in linking systemic support to AI implementation: external support is insufficient without teacher readiness, while individual capacity is most impactful within a supportive ecosystem. Table 8 confirms the model's assumption of partial mediation.

Table 8. Summary of hypothesis testing results

Hypothesis	Path	Findings	Interpretation
H_1	External Factors → Internal Factors	Supported ($\beta = 0.275$, $p < 0.001$)	Educational policies, infrastructure, and community support significantly enhance teachers' readiness.
H_2	Internal Factors → AI Utilization	Supported ($\beta = 0.791$, $p < 0.001$)	Pedagogical readiness, TPACK mastery, and positive attitudes predict effective AI adoption.
H_3	External Factors → AI Utilization (indirect)	Indirect effect supported via Internal Factors ($\beta = 0.217$, $p < 0.001$); direct effect not significant	External factors influence AI use only when mediated by internal teacher capacity.

This model reflects a fully mediated structure, where the impact of external factors on AI adoption occurs entirely through teachers' internal readiness. Aligned with the E-TPACK and Technology Acceptance Model (TAM), this finding underscores that technology adoption is shaped not only by perceived utility but by the interaction between individual preparedness and systemic support. Model robustness was confirmed through sensitivity analysis (±10% variation) and alternative model testing, with negligible effects on path coefficients, R^2, and Q^2, indicating strong stability. The results reaffirm TAM's emphasis on attitudes and perceptions and highlight the importance of integrating technological, pedagogical, and content knowledge as outlined in TPACK. Within the E-TPACK framework, the synergy between internal readiness and external support is pivotal for effective AI integration. Practically, the findings call for education policies that go beyond infrastructure provision, focusing instead on strengthening pedagogical competencies, enhancing digital literacy, and supporting community-based implementation. Prioritizing targeted AI training and curriculum adaptation can foster a more holistic, adaptive, and sustainable digital transformation in primary education.

Discussion

Table 8 summarizes the hypothesis testing results derived from the second-order structural model analyzed using SmartPLS 4.0. The model integrates the TPACK framework (Mishra et al., 2023), the Technology Acceptance Model (Davis & Granić, 2024), and the ecological E-TPACK approach. Internal factors are modeled as a second-order reflective construct comprising attitudes toward AI and TPACK competence, while external factors include educational policy, digital infrastructure, and community support. Construct validity is supported by satisfactory AVE, rho_A, and HTMT values. The model demonstrates good fit, with an SRMR of 0.036, well below the 0.08 threshold. Harman's single-factor test also indicates no significant common method bias, as no single factor explained more than 50% of the variance, confirming the model's robustness.

The systemic impact of external factors on teachers' internal readiness for AI integration in primary mathematics education

The findings of the analysis demonstrate that external factors exert a statistically significant and positive influence on internal factors ($\beta = 0.275$; $T = 9.706$; $p < 0.001$; $f^2 = 0.12$; $R^2 = 0.39$), suggesting a moderate effect on teachers' internal preparedness, characterized by favorable attitudes toward artificial intelligence and proficiency in TPACK. This internal readiness is not developed in isolation; rather, it is shaped by the presence of enabling policies, reliable digital infrastructure, and the active engagement of parents and the wider community. These results substantiate Bronfenbrenner's ecological systems theory (Davis & Granić, 2024), which asserts that human development is deeply embedded within and influenced by multilayered socio-ecological systems. Within the context of AI integration in education, external elements function both as structural enablers and as catalysts for psychological preparedness. This aligns with insights from Flores-Vivar and García-Peñalvo (2023), who underscore the importance of institutional scaffolding in alleviating teacher resistance to AI, and Yue et al. (2024), who emphasize that effective leadership and community collaboration are vital to strengthening teachers' readiness. Unlike theoretical models that narrowly emphasize individual competencies (Mishra et al., 2023; Sun & Chen, 2023), the present study advances a more holistic perspective, positing that successful AI adoption in primary education is fundamentally shaped by the synergistic interaction between educational policy, technological capacity, and sociocultural conditions.

The influence of internal factors on AI utilization in primary mathematics instruction

The structural model assessment revealed that internal determinants specifically teachers' attitudes toward artificial intelligence and their TPACK competencies exerted a robust and statistically significant influence on the integration of AI within primary mathematics instruction ($\beta = 0.791$, $T = 16.523$, $p < 0.001$; 95% CI [0.692, 0.870]; $f^2 = 0.56$). Internal readiness was found to explain 68% of the variance in AI utilization ($R^2 = 0.68$), signifying a substantial level of predictive accuracy following the criteria outlined by Hair and Alamer (2022). These findings empirically validate the core propositions of the Technology Acceptance Model (Davis & Granić, 2024) while simultaneously highlighting the pivotal function of TPACK in guiding the pedagogical and technological integration of AI tools (Celik, 2023; Mishra et al., 2023). Thus, effective and sustainable implementation of AI in educational settings is contingent not merely upon teachers' positive dispositions but also upon their capacity to ethically and pedagogically embed AI into instruction that fosters meaningful student learning.

These results align with studies by Yue et al. (2024) and Khong et al. (2023), which identified teachers' attitudes and TPACK competencies as key predictors of post-pandemic readiness. However, unlike previous research that focused broadly on educational technologies, this study specifically highlights the unique complexities of AI, including automation, personalization, and ethical implications (Chen, 2020; Flores-Vivar & García-Peñalvo, 2023). As such, strengthening AI literacy and developing teachers' TPACK should be prioritized in digital education transformation. Teacher training must evolve beyond technical instruction to encompass holistic and reflective approaches, including AI-based simulations, adaptive learning scenarios, and digital ethics development. This aligns with the Intelligent-TPACK framework (Celik, 2023), which emphasizes the integration of digital competence with ethical considerations in classroom-based AI applications. Although internal factors were found to be dominant, the findings also highlight the essential role of external support. Without enabling policies, adequate infrastructure, and cross-sector collaboration, teachers' potential to harness AI effectively may be limited (Bronfenbrenner, 1986; Zhao, 2024). Therefore, sustainable AI integration in education requires a strong synergy between teachers' internal capacities and a robust system of external support.

Direct and indirect effects of external factors on AI utilization

The analysis revealed that the direct effect of external factors on teachers' utilization of AI was statistically insignificant ($\beta = 0.008$, $T = 0.115$, $p = 0.908$). However, there was a significant indirect effect mediated by internal factors ($\beta = 0.217$, $T = 3.872$, $p < 0.001$; 95% CI [0.112, 0.326]), emphasizing the crucial role of teachers' internal readiness in bridging the influence of external environments. These findings reinforce (Bronfenbrenner, 1986)'s ecological theory, which posits that environmental influences on individuals are mediated by internal characteristics. In this context, TPACK competence, AI literacy, and self-efficacy emerge as the primary mediators (Celik, 2023; Mishra et al., 2023). This implies that external interventions, such as generic training, provision of devices, or policy implementation, will likely be ineffective without a parallel reinforcement of teachers' internal capacities. Antonenko and Abramowitz (2023) further observed that misconceptions about AI can foster resistance, even when infrastructural and policy support is present. From a practical standpoint, capacity-building strategies must include AI-based TPACK development (Gagne et al., 2021; Mishra et al., 2023), critical digital literacy (K. K. H. Ng et al., 2021; Walter, 2024), and enhancing self-efficacy and motivation within digital learning environments (Yue et al., 2024). Context-sensitive and personalized approaches are considered more effective than uniform institutional interventions (Ahmad et al., 2021; Pineda-Martínez et al., 2023).

Given the significant mediation path, teachers should not be viewed merely as policy recipients but as reflective pedagogical agents who ethically and contextually adapt AI in the classroom (El Hajj & Harb, 2023; Gadanidis, 2017). Consequently, AI integration policies must be designed holistically, addressing the cognitive, affective, and conative dimensions of teacher development (Chen, 2020; Hwang & Tu, 2021). The divergence from prior studies that emphasized external interventions (Guo & Wan, 2022; Khong et al., 2023) underscores the need for a paradigm shift. Interventions should focus on empowering teachers' adaptive capacities to navigate rapidly evolving digital ecosystems (Annuš & Kmeť, 2024; Sutrisman et al., 2024), including understanding the ethical and social implications of AI use (Bibri & Allam, 2022; Flores-Vivar & García-Peñalvo, 2023). In this regard, internal factors are not merely supplementary but rather serve as the leverage point of AI adoption in education. Meaningful digital transformation in the classroom can only be achieved by prioritizing internal teacher capacity-building over external provisioning or regulation.

Implications of the study

The findings highlight that integrating AI into elementary mathematics education requires a strategic synergy between external support and teachers' internal capacities. In alignment with the E-TPACK framework, external factors, such as supportive policies, equitable digital infrastructure, and community involvement, serve as critical prerequisites. However, the successful implementation of AI ultimately hinges on strengthening teachers' internal competencies, particularly AI-enhanced TPACK and ethical technology literacy. Professional development programs should be modularly designed to include: (1) adaptation of the mathematics curriculum using locally relevant AI tools such as GeoGebra AI or Scribe AI; (2) ethical-pedagogical exploration through AI-assisted flipped microteaching; and (3) collaborative reflection via digital lesson study. Furthermore, the development of peer coaching systems within schools plays a vital role in fostering pedagogical autonomy and teacher confidence.

Nevertheless, AI integration also poses critical challenges. Without reflective practice, AI risks reducing teachers to mere technology operators. Dependence on proprietary algorithms, the dominance of foreign vendors, and potential systemic biases threaten to erode local values embedded within national curricula (Bibri & Allam, 2022). Therefore, technology adoption should prioritize open-source accessibility, interoperability, and cultural and linguistic relevance. On a global scale, these findings are particularly relevant to developing countries in ASEAN and Africa, which face parallel challenges such as infrastructure inequality, limited access to meaningful training, and the pressures of technological globalization. A promising recommendation lies in the design of micro-AI-integrated MOOCs, which offer just-in-time, teacher-centered learning experiences, paving the way for adaptive, ethical, and equitable AI integration in education.

Limitations and future research

This study has limited generalizability as it focuses solely on elementary mathematics teachers in urban Jakarta, an area that typically benefits from better access to digital infrastructure, technology training, and professional learning communities. As such, the findings do not capture the substantial disparities faced by rural schools, including limited connectivity, low AI literacy, and institutional differences among public schools, Islamic madrasahs, and inclusive private institutions. Moreover, the cross-sectional design presents epistemological limitations, as it provides only a snapshot in time and fails to track the progression of teacher competencies post-training or their responses to ongoing curricular and technological shifts in the post-pandemic landscape.

Another limitation lies in the study's monodisciplinary focus on mathematics education. The integration of AI in other disciplines, such as literacy, science, and inclusive education, poses unique pedagogical and ethical challenges, particularly in terms of content adaptability, the validity of AI-driven assessments, and students' affective responses. Future research should adopt experimental and longitudinal approaches, including the development of an AI literacy framework tailored for elementary educators, structured trials of TPACK+AI-based training programs, and critical analyses of algorithmic bias and its impact on marginalized student populations. Normative discussions on the ethical use of AI in primary education are also essential, particularly concerning child data privacy, student digital agency, and the urgent need for protective state regulation. Additionally, the functional integration of MOOCs and AI warrants investigation, especially regarding their potential to enhance personalized learning, scaffolding, and adaptive feedback for teachers with limited digital literacy. In summary, future research agendas must not only broaden empirical scope but also drive systemic transformation toward an AI-integrated educational ecosystem that is inclusive, ethical, and contextually grounded. AI-based educational research must move beyond passive adaptation to technology and instead serve as a vehicle for educational justice in the digital age.

Conclusion

This study concludes that the successful adoption of Artificial Intelligence (AI) in elementary mathematics education depends on the synergistic interplay between teachers' internal readiness, particularly their attitudes and TPACK proficiency, and external systemic support. The E-TPACK model, combining TPACK, TAM, and ecological systems theory, demonstrated strong empirical validity and predictive relevance, explaining 78.1% of the variance in AI utilization. Internal factors were the most decisive, while external factors played a supporting role by enhancing internal capacities. Theoretically, this research refines and contextualizes the TPACK framework through an ecological lens, offering a more holistic approach to educational technology integration. Practically, it emphasizes the need for targeted teacher training and inclusive digital policy frameworks. However, the study is limited by its urban focus and the absence of cross-institutional analysis. Future research should explore rural and underserved contexts while addressing digital equity, algorithmic bias, and data privacy to ensure inclusive and ethical AI integration in primary education.

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Conflicts of Interest

The authors declare no conflict of interest regarding the publication of this manuscript. All ethical considerations related to the research and publication process, such as plagiarism, research misconduct, data fabrication or falsification, duplicate publication or submission, and redundancy, have been thoroughly addressed and complied with.

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Author Contributions

Dwi Yulianto: Conceptualization, methodology, supervision, writing – original draft, visualization, project administration; **Rahmat Nurcahyo**: Formal analysis, software, data curation, writing – review & editing, validation; **Yusup Junaedi**: Resources, investigation, writing – review & editing; **Astari**: Instrument development, software testing, and technical support; **Egi Adha Juniawan**: Funding acquisition, ethical validation, and administrative coordination.

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