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DETERMINANTS OF INDONESIAN PRIMARY TEACHERS' ADOPTION OF ARTIFICIAL INTELLIGENCE IN SCIENCE TEACHING

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Abstract. The integration of artificial intelligence (AI) in education has gained increasing attention; however, its adoption in elementary science teaching remains uneven. This study aims to evaluate the factors influencing Indonesian elementary school teachers' adoption of AI in science teaching by extending the Technology Acceptance Model (TAM). An exploratory quantitative research design was employed involving 322 elementary school science teachers in Indonesia. Data were collected using a structured questionnaire that measured six latent constructs: Perceived Usefulness, Perceived Ease of Use, Attitude Toward Use, Behavioral Intention, Self-Efficacy, and AI Anxiety. The data were analyzed using structural equation modeling. The findings revealed that perceived usefulness was the strongest predictor of teachers' behavioral intention to adopt AI in science teaching. In addition, self-efficacy and AI anxiety significantly influenced teachers' perceptions and attitudes toward AI integration. These results indicate that AI adoption in elementary science education is shaped not only by technological perceptions but also by psychological and pedagogical factors, including teachers' confidence and learning experiences. This study extends the TAM framework by integrating psychological antecedents in a developing country context and provides theoretical and practical insights for developing teacher-centered strategies to support effective AI integration in elementary science teaching.

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INTRODUCTION

Artificial intelligence (AI) has transformed industries across the board, including primary school instruction. Educational technology has made AI a cutting-edge learning tool. It can remodel course design, instruction, and grading (Adiguzel et al., 2023). Using learning tools, elementary school teachers' willingness to incorporate AI is as important as the equipment (Jang et al., 2022; Xu & Ouyang, 2022). Elementary science teachers make a big difference in kids' scientific literacy (Deehan et al., 2024). Elementary school teachers in Indonesia face several hurdles when integrating AI into the science curriculum. A lack of infrastructure, technology, and teacher preparation hinders the application of AI in elementary schools, despite the Ministry of Education's goal of revolutionizing digital education through national policy (Dai, 2024). This issue raises fundamental questions about Indonesian primary school teachers' use of AI in science education.

International studies have examined teacher AI uptake using the Technology Acceptance Model (TAM) and its expansions. Research in Africa demonstrates that science teachers accept AI for its perceived simplicity of use and usefulness (Nja et al., 2023). International studies have examined educator acceptance of AI using the Technology Acceptance Model (TAM) and its expansions. Performance is important in China, in Africa, and science teachers are open to AI because they think it is useful and easy to use, and how society and achievement expectations affect elementary school teachers' decisions to use AI (An et al., 2023). In Indonesia, the education system, elementary school culture, and technology preparation vary, so these conclusions are not totally relevant.

Accordingly, this study primarily examines science teachers in Indonesian elementary schools, aiming to identify factors influencing the adoption of artificial intelligence in elementary science teaching through the extended Technology Acceptance Model (TAM) framework. This study is structured as an analysis of instructional technology in elementary school science education, rather than as a conventional evaluation of science materials. This study aims to address the following research question, grounded in the research background, objectives, and the comprehensive TAM theoretical framework: 1) How do Indonesian primary teachers adopt artificial intelligence in science teaching? 2) How does Perceived Usefulness influence primary teachers' attitudes and behavioral intentions to adopt AI in science teaching? 3) Does perceived usefulness affect elementary school teachers' AI views? 4) How do Indonesian elementary school science teachers' AI self-efficacy and anxiety affect AI adoption? 5) How much does Attitude Toward Use change the behavioral intention to use AI in teaching elementary science?

The present study examines six core constructs: Perceived Usefulness, Perceived Ease of Use, Attitude Toward Use, Behavioral Intention, Self-Efficacy, and AI Anxiety, which are theoretically and empirically posited to influence AI adoption among primary school teachers in elementary science instruction. Research variables and theory are defined as follows: In elementary science education, Perceived Usefulness (PU) refers to the degree to which AI helps teachers explain abstract scientific concepts, visualize scientific processes, conduct adaptive assessments, and improve learning efficiency (Zhang & Zhang, 2024). Primary school teachers who recognize AI as a technology that effectively supports instructional objectives in scientific education are more inclined to cultivate favorable attitudes and to adopt it. The 1st Hypothesis (H1): Perceived Usefulness positively and significantly influences primary school teachers' Attitude Toward Use of AI in elementary science education. The 9th Hypothesis (H9): Perceived Usefulness positively and significantly influences primary school teachers' Behavioral Intention to adopt AI in elementary science education.

Perceived Ease of Use (PEOU) indicates how easy primary school educators perceive using AI in elementary science instruction to be, and whether it is low-effort and does not increase their workload (Almogren et al., 2024). The 2nd Hypothesis (H2): Perceived Ease of Use positively and significantly influences the Perceived Usefulness of AI in elementary science education. The 3rd Hypothesis (H3): Perceived Ease of Use positively and significantly influences primary school teachers' Attitude Toward Use of AI. The 10th Hypothesis (H10): Attitude towards Use mediates a positive, significant relationship between Perceived Ease of Use and elementary school teachers' Behavioral Intention to adopt AI.

An elementary school teacher's attitude toward usage (ATU) of AI in scientific instruction indicates whether they find the technology favorable, beneficial, and pleasant. Attitude mediates the relationship between cognitive beliefs, such as PU and PEOU, and BI in the TAM and TRA (Bali et al., 2025). The 4th Hypothesis (H4): Attitudes towards use have a positive and significant impact on elementary school teachers' behavioral intentions to adopt AI in science education.

Behavioral Intention (BI) refers to the degree of primary school teachers' readiness and willingness to use and continuously integrate AI into elementary science instruction. In the TRA and the TAM, BI is identified as the foremost predictor of actual technology usage behavior (Li, 2023). In the context of elementary science education, BI reflects teachers' preparedness to shift from conventional instructional approaches toward AI-supported learning as an instructional tool. Relevant hypotheses include H4, H9, and H10.

Elementary school teachers' self-efficacy (SE) is their belief in their ability to study, apply, and incorporate AI into science (Yang et al., 2024). High self-efficacy primary school teachers perceive AI as an opportunity to advance scientific instruction, not a hindrance. The 5th Hypothesis (H5): Self-Efficacy positively and significantly influences primary school teachers' Perceived Ease of Use of artificial intelligence in elementary science instruction. The 6th Hypothesis (H6): Self-Efficacy positively and significantly influences primary school teachers' Perceived Usefulness of artificial intelligence in elementary science instruction.

AI in elementary science may make teachers nervous, afraid, or uncomfortable. Anxiety comes from technology, mistakes, and AI replacing teachers (Karataş & Yüce, 2024). In the context of AI as an educational technology, high levels of anxiety about AI may hinder elementary school teachers' readiness to integrate it into science instruction. The 7th Hypothesis (H7): AI

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Anxiety (AIA) negatively and significantly affects Perceived Ease of Use of AI. The 8th Hypotheses (H8): AI Anxiety has a negative and significant effect on primary school teachers' Attitude Toward Use of AI. Overall, Figure 1 shows the proposed research model with ten hypotheses.

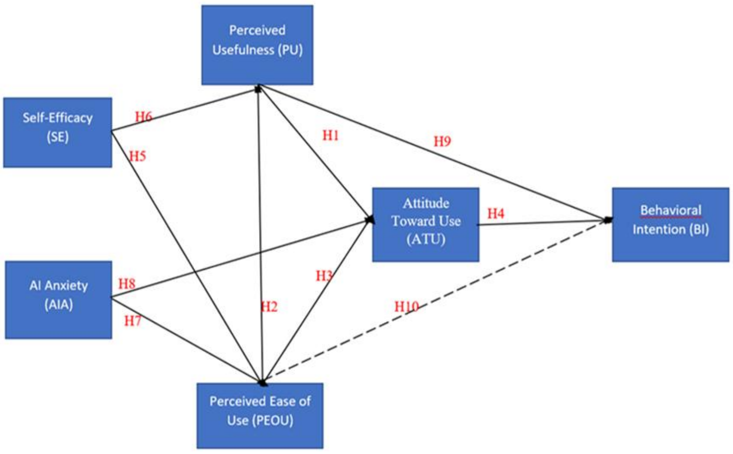

Figure 1. Research proposed model

RESEARCH METHODS

This quantitative explanatory study examined Indonesian science instructors' AI incorporation in science instruction. To study possible causal relationships between TAM and extension notions, an explanatory method was chosen. This study examined how cognitive, affective, and psychological factors influence science teachers' intentions to integrate AI. The TAM-based study model includes latent variables for PU, PEOU, ATU, BI, SE, and AIA. PU and PEOU are TAM fundamentals; ATU mediates; SE and AIA are external psychological antecedents. The problematic process by which elementary school science teachers accepted AI was explored using 11 assumptions (Uyanik, 2025). This survey included 322 primary teachers. The sampling procedure included these criteria: 1) Elementary school teachers, 2) Teachers who comprehend digital technologies, and 3) Volunteer teachers for this study.

Data was collected using a TAM and AI adoption study-based questionnaire for Indonesian primary science education (Pratama et al., 2025). Questions include two parts: 1) Demographic data like grade level, learning experience, and AI learning tool knowledge. 2) Research Variables PU, PEOU, ATU, BI, SE, and AIA are measured per setup. Items on Likert scales range from one (dissatisfied) to five (content). Each item is contextualized for elementary school and teacher training. Before hypothesis testing, the measurement model construct validity and reliability were validated. Composite Reliability, AVE, and factor loadings assessed convergence (Hair & Alamer, 2022). Fornell–Larcker and cross-loading study tested discriminant validity (Rasoolimanesh, 2022).

PLS-SEM was used to analyze the data (Legate et al., 2024). Two steps were taken for analysis: 1) Measurement Model Evaluation, assessing construct dependability and validity. 2) Structural Model Evaluation, examining path coefficients, coefficient of determination (R^2), effect sizes (f^2), predictive relevance (Q2). Hypotheses are tested by assessing the significance of path coefficients via bootstrapping, with an appropriate number of resamples to ensure robust statistical inference.

RESULTS AND DISCUSSION

Figure 2 shows the original Partial Least Squares (PLS) path model of the latent construct structural linkages in the Extended Technology Acceptance Model. SE, AIA, PEOU, PU, ATU, and BI are linked in this model to explain Indonesian elementary school science teachers' adoption of AI. This model separates exogenous (SE and AI) and endogenous (PEOU, AI, ATU, and BI) constructs using PLS-SEM. The PLS-SEM methodology prioritizes maximizing R^2 of significant dependent variables over overall model fit. Figure 2 illustrates how SE and AIA affect teachers'

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AI choices. Garson's first PLS path model interpretation emphasizes structural configuration, direction of relationships, and explained variance, whereas later hypothesis testing assesses the statistical significance of the paths. This research uses a theoretically valid and methodologically adequate initial structural model (Figure 2) to assess measurement models and test structural hypotheses.

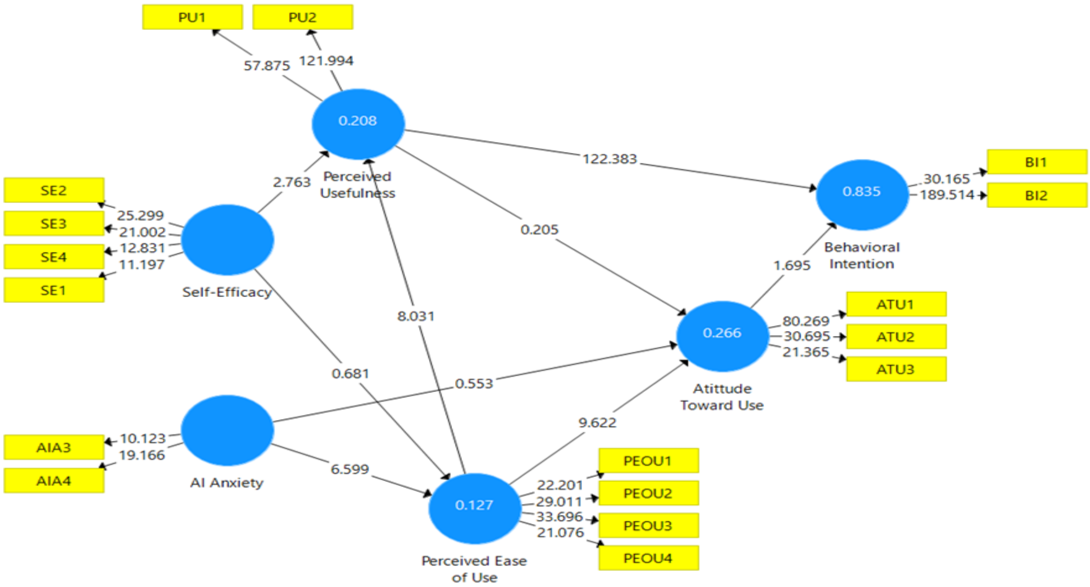

Figure 2. Initial PLS Path Model

All latent constructs in the measurement model were evaluated for convergent validity and reliability in Table 1. CR measured internal consistency reliability, whereas external loadings and AVEs measured convergent validity. In Table 1, all measurement items have loadings above 0.70 on the outside loadings, indicating sufficient internal consistency. Each indicator appropriately represents its construct with external loadings from 0.742 to 0.931. All constructions have CR values above 0.70, ranging from 0.790 to 0.914. The constructions have high internal consistency reliability. All constructs had AVE values above 0.50, ranging from 0.632 to 0.842, indicating that each one accounts for more than 50% of its indicators' variance.

Table 1. Convergent validity-Reliability

Construct	Item	Outer Loading	Composite Reliability	Average Variance Extracted (AVE)
AI Anxiety (AIA)	AIA3	0.744	0.790	0.655
	AIA4	0.869		
Attitude Toward Use (ATU)	ATU1	0.899	0.882	0.715
	ATU2	0.855		
	ATU3	0.777		
Behavioral Intention (BI)	BI1	0.831	0.872	0.774
	BI2	0.926		
Perceived Ease of Use (PEOU)	PEOU1	0.785	0.873	0.632
	PEOU2	0.833		
	PEOU3	0.814		
	PEOU4	0.744		
Perceived Usefulness (PU)	PU1	0.903	0.914	0.842
	PU2	0.931		
Self-Efficacy (SE)	SE2	0.859	0.895	0.681
	SE3	0.887		
	SE4	0.806		
	SE1	0.742		

Table 2 displays Fornell–Larcker-based discriminant validity results. When each construct's square root of the AVE exceeds its association with others, discriminant validity is

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verified. Table 2 shows that the square roots of the AVE values (diagonal elements) for AIA, ATU, BI, PEOU, PU, and SE exceed their inter-construct correlation coefficients. The indicators of each construct vary more than those of other constructs in the model. The correlation between constructs is adequate and not particularly high. It appears that the measurement model does not have multicollinearity. Table 2 shows that all constructs are empirically distinct and assess different aspects of Indonesian primary teachers' use of AI in science instruction, proving that the measurement model is discriminant. These findings confirm the suitability of the measurement approach for structural model evaluation.

Table 2. Discriminant validity

	AIA	ATU	BI	PEOU	PU	SE
AIA	**0.809**					
ATU	0.146	**0.845**				
BI	0.659	0.152	**0.880**			
PEOU	0.354	0.514	0.435	**0.795**		
PU	0.705	0.206	0.913	0.428	**0.918**	
SE	0.342	0.066	0.202	0.085	0.192	**0.825**

Table 3 presents the PLS-SEM findings for the structural model hypothesis testing. Standardized route coefficients (β), t-values, and bias-corrected confidence intervals were obtained using bootstrapping to evaluate hypothesized associations. Study confirms favorable influence of PEOU on PU (β = 0.415, t = 7.668) and ATU (β = 0.525, t = 9.774), supporting H2 and H3. A significant impact of PEOU on BI (β = 0.362, t = 7.014) supports H10. Positive influence of PU on BI (β = 0.921, t = 127.446) supports H9. PU has no significant impact on ATU (β = 0.019, t = 0.215), rejecting H1. SE positively affects PU (β = 0.157, t = 2.871), supporting H6, but not PEOU (β = -0.040, t = 0.655), rejecting H5. PEOU is significantly impacted by AIA (β = 0.368, t = 6.059), supporting H7. There is no significant effect on ATU (β = -0.053, t = 0.540), rejecting H8. Significant effect of ATU on BI is not observed (β = -0.038, t = 1.627), rejecting hypothesis 4. Table 3 supports seven of the 10 hypotheses, emphasizing the role of cognitive beliefs, notably PU and PEOU, in explaining Indonesian elementary school teachers' BI regarding the use of AI in science education.

Table 3. Summary Hypotheses Testing

Hypotheses	Path	Std. betta (β)	Std. error	t-value	Confidence intervals bias corrected			Decision
					Bias	5.0%	95.0%	
H1	PU -> ATU	0.019	0.087	0.215	0.001	-0.123	0.167	Rejected
H2	PEOU -> PU	0.415	0.054	7.668	0.003	0.318	0.494	Supported
H3	PEOU -> ATU	0.525	0.054	9.774	0.006	0.428	0.603	Supported
H4	ATU -> BI	-0.038	0.024	1.627	-0.001	-0.079	-0.002	Rejected
H5	SE -> PEOU	-0.040	0.062	0.655	0.004	-0.151	0.043	Rejected
H6	SE -> PU	0.157	0.055	2.871	0.004	0.055	0.237	Supported
H7	AIA -> PEOU	0.368	0.061	6.059	0.001	0.255	0.461	Supported
H8	AIA -> ATU	-0.053	0.098	0.540	0.000	-0.199	0.122	Rejected
H9	PU -> BI	0.921	0.007	127.446	0.001	0.909	0.933	Supported
H10	PEOU -> BI	0.362	0.052	7.014	0.003	0.268	0.436	Supported

Table 4 displays R^2 and adjusted R^2 values for endogenous constructs in the structural model. The R^2 value measures the model's predictive ability by indicating the proportion of variance in each endogenous construct explained by exogenous factors. In Table 4, behavioral desire explains 83.5% of Indonesian primary teachers' desire to integrate AI in scientific instruction, with an R^2 value of 0.835 (adjusted R^2=0.834). These findings show strong explanatory power for the study's primary variables. The model's antecedents explain 26.6% of teachers' AI attitudes. Their explanatory power is average, with a R^2 value of 0.266 (adjusted R^2 = 0.259). The R^2 for PU is 0.208 (adjusted R^2 = 0.203), indicating that the predictors account for 20.8% of the variance in instructors' AI usability ratings. The psychological model explains 12.7% of PEOU variation, with an R^2 of 0.127 (adjusted R^2 of 0.121). The R^2 values in Table 4 show that the structural model explains BI with significant power and other endogenous dimensions with moderate power. Data

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suggest the Extended TAM explains Indonesian elementary school science teachers' AI use.

Table 4. R^2 is the coefficient of determination

	R Square	R Square Adjusted
ATU	0.266	0.259
BI	0.835	0.834
PEOU	0.127	0.121
PU	0.208	0.203

Table 5 displays effect size (f^2) values for each structure link in the model. The f^2 statistic evaluates the influence of an exogenous construct on an endogenous construct by measuring the change in R^2 after its subtraction from the model. According to Table 5, PU significantly affects teachers' intention to apply AI in scientific education ($f^2 = 4.927$). These data demonstrate the structural model's utility focus. PEOU has a significant impact on teachers' perspectives on AI, with a moderate effect size on PU ($f^2 = 0.216$) and a big effect size on ATU ($f^2 = 0.305$). A minor effect of AIA was observed on PEOU ($f^2 = 0.137$) but not on ATU ($f^2 = 0.002$). SE had a negligible effect on PU ($f^2 = 0.031$) and PER ($f^2 = 0.002$). The limited impact of ATU on BI ($f^2 = 0.009$) suggests a modest contribution to the model's explained variance. In Table 5, the f^2 values indicate that PU and PEOU are the most significant predictors. Other constructs have little effect on endogenous variables.

Table 5. f^2 is the effect size

AIA	ATU	BI	PEOU	PU
AIA	0.002		0.137	
ATU		0.009		
BI				
PEOU	0.305			0.216
PU	0.000	4927		
SE			0.002	0.031

Table 6 displays the predictive relevance (Q^2) of the blindfolded structural model. The Q^2 statistic evaluates the model's ability to predict endogenous construct values. A Q^2 score above zero reflects the model's predictive power for a specific construct. Table 6 demonstrates that the suggested model is predictive, with all endogenous constructs having Q^2 values above zero. The model's high Behavioral Intention score ($Q^2 = 0.620$) indicates its ability to predict Indonesian elementary school teachers' usage of AI in science instruction. Instructional mental judgments of AI are modestly impacted by ATU ($Q^2 = 0.175$) and PU ($Q^2 = 0.171$). Low but moderate predictive relevance for AI ease of use perceptions is indicated by a Q^2 score of 0.080.

Table 6. Q^2 is predictive relevance

	Q^2 (=1-SSE/SSO)
AIA	
ATU	0.175
BI	0.620
PEOU	0.080
PU	0.171
SE	

The measurement model evaluation results (Tables 1 and Table 2) indicate that all constructs exhibit satisfactory convergent and discriminant validity, suggesting that the instruments accurately capture distinct aspects of AI adoption among primary teachers. Effective operationalization is indicated by high Composite Reliability, significant outer loading, and sufficient AVE scores. Prior research suggests this. Kamarudin et al. (2024) and Mohd Dzin & Lay (2021) confirmed that the appropriate operationalization of these constructs is substantially supported by strong external factors, high Composite Reliability indices, and adequate AVE values. The robustness of this measurement enhances the credibility of subsequent structural model findings and aligns with the PLS-SEM criteria recognized in educational technology research. The results of the structural model (Table 3) indicate that PU is the most significant predictor of BI to utilize AI in science education. Similar findings from research by Al Darayseh

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(2023) indicate that the construct of PU emerges as the most significant predictor of BI to utilize artificial intelligence (AI) in science education. The very strong path coefficient from PU to BI indicates that elementary school teachers in Indonesia are primarily motivated by instrumental considerations, particularly regarding whether AI is perceived to significantly improve teaching effectiveness and students' understanding of science (Park et al., 2023).

This study supports the TAM's main finding that perceived utility is the best predictor of technology adoption and highlights elementary school teachers' pragmatic approach to technology assessment. PU strongly affected AI but had little effect on ATU. This model shows that elementary science teachers' adoption of AI is driven by rational assessments of educational benefits rather than emotional responses. The study by Yao & Abd Halim (2023) revealed that, In the domain of elementary science education, teachers' intentions to use artificial intelligence (AI) are influenced more by rational appraisals of its instructional usefulness than by affective or emotional concerns. Professional teaching may prioritize pedagogical efficacy and curricular objectives over personal preferences, according to the TAM. Usability inspired this. The high impact of PEOU on PU, ATU, and BI implies that ease of use improves instructors' AI evaluations and inspires them to use it. Teachers employ smart, teacher-friendly AI tools in science classes. A study by Kotsis (2024) also found that AI helps teachers teach science.

Findings regarding psychological antecedents offer complex insights. SE strongly influenced PU, but not PEOU, demonstrating that teachers' confidence in adopting technology boosted their assessments of AI's instructional value rather than its ease of use. Self-efficacy helps teachers see instructional benefits even when AI tools seem complicated. ATU is unaffected by AIA, while PEOU is. This suggests that anxiety affects instructors' ratings of usability rather than their overall AI evaluation. According to findings Ayanwale et al. (2022), the primary purpose of this study was to improve teachers' perceptions of the ease of use of artificial intelligence (AI) rather than to assess their overall knowledge of the technology. This discrepancy highlights the need to address emotional barriers to AI adoption through professional development. The model R^2 values (Table 4) provide further context for interpretation. The model explains 83.5% of the variance in Behavioral Intention, implying that the identified determinants provide a robust explanatory framework for AI adoption among elementary teachers. The moderate R^2 values for PU, ATU, and PEOU indicate that the model captures the essential drivers, although additional contextual factors, such as institutional support or policy alignment, may further influence teachers' perceptions and attitudes (Tomczyk & Majkut, 2025).

PU and PEOU are crucial to the model, as shown by effect size analysis (Table 5). The considerable impact of PU on BI drives adoption intention. PEOU shows that making something easy to use boosts cognitive and emotional abilities by affecting PU and ATU. Low SE and AIA effects suggest psychological factors are buffers rather than primary factors. Chen et al. (2025) also suggest that SE and AIA encourage technology adoption indirectly rather than actively predicting it. Finally, the predictive relevance results (Table 6) show that the model has very good predictive power, especially for Behavioral Intention. BI has a high Q^2 value in the extended TAM model, indicating its explanatory and predictive properties. This strength highlights the model's potential to build on past efforts to promote AI in elementary school science teaching. Consistent with the findings of Kavitha & Joshith (2025), a high Q^2 score for AI indicates strong predictive relevance, underscoring the importance of AI adoption in improving teachers' instructional performance. Overall, the findings of this study add to the literature on AI adoption in education by demonstrating that elementary school teachers' adoption of AI in science teaching is primarily influenced by perceived instructional benefits and ease of use, rather than affective attitudes. From the perspective of technology learning in elementary school science education, these findings indicate that successful AI integration depends on the design of AI tools that clearly support pedagogical goals, are easy to use, and are accompanied by professional development that enhances teacher confidence and reduces anxiety.

CONCLUSIONS AND SUGGESTIONS

This study provides new empirical evidence on Indonesian primary teachers' use of

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artificial intelligence in scientific education, indicating that technology adoption decisions are mostly influenced by perceived instructional value and usability rather than affective attitudes. Using the TAM to examine psychological factors, we can see that PU is the most important predictor of behavioral intention, while PEOU is the most important predictor of long-term adoption effects. Importantly, this study found a more complex relationship between ATU and adoption behavior, driven by affect and pragmatism among elementary school teachers, which is consistent with the assumptions of classical TAM. Recent research found that SE increased value recognition and AIA decreased PU. This sheds light on how psychology affects the use of AI in primary school science.

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