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From Vision to Innovation: How Digital Leadership and Technological Competence Influence AI-Based Learning through Teacher Efficacy

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ABSTRACT. Artificial intelligence (AI) is becoming more common in educational practice, particularly in personalized instruction, adaptive feedback, and data-informed teaching. Its effective and ethical use, however, requires more than access to digital tools. Institutional leadership, teachers' technological competence, and their confidence in applying AI to teaching also play important roles. This study examines how digital leadership and teachers' technological competence relate to AI-based learning, with teacher efficacy as a mediating variable. A quantitative cross-sectional survey was conducted with 222 teachers, and the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The measurement model was evaluated in terms of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Mediation effects were examined through bootstrapping. The results show that digital leadership and technological competence have positive and statistically significant direct relationships with AI-based learning. Both variables are also positively related to teacher efficacy, which is itself positively associated with AI-based learning. Teacher efficacy partially mediates the relationships of digital leadership and technological competence with AI-based learning. These findings suggest that the implementation of AI in education is closely linked to institutional support, teachers' technological capabilities, and their confidence in using these technologies. Educational institutions can support this process by strengthening digital leadership, developing teachers' technological and pedagogical competencies, and fostering teacher efficacy through coaching and reflective professional development. Such efforts can help create conditions for the responsible and effective use of AI in teaching and learning.

Keywords: *Educational Technology; Artificial Intelligence in Education; Digital Leadership; Teacher Efficacy; Professional Development; Digital Competence.*

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INTRODUCTION

The use of Artificial Intelligence (AI) in education has expanded across different educational levels, accompanied by growing research interest and the adoption of technologies that support personalized learning, adaptive assessment, and data-driven instructional decisions (Chairawati et al., 2026; Crompton & Burke, 2023; Indasari, 2026; Kayyali, 2024; Sutrisno et al., 2025). This development involves more than technological progress; it also influences how teaching and learning are designed and carried out (Ahmad Kusaini et al., 2024; Ayu et al., 2025; Badawi, 2025; Bahri et al., 2026). AI enables learning experiences to be adjusted to students' individual needs, making it increasingly relevant to educational practice (Khastgir & Shalini, 2024; Wale, 2024). As

digital platforms become more accessible, research on AI in education has also moved beyond its initial focus on higher education students to include a broader range of educational stakeholders (Mustafa et al., 2024). This broader focus calls for an examination of AI's role across different levels of education, including its implications for teachers, school leaders, and institutional policies, rather than focusing solely on student outcomes.

Despite its potential to improve students' learning experiences, the use of AI in education still presents challenges, particularly in teachers' digital and pedagogical literacy and their ability to integrate technology effectively and ethically into classroom practice (Reina Marín et al., 2025). AI literacy extends beyond technical knowledge; it also requires teachers to understand how AI can support teaching and learning in meaningful ways. Previous studies have examined aspects of this issue from different perspectives, including the relationship between digital leadership and teachers' technology integration during the COVID-19 pandemic in Kuwait (AlAjmi, 2022), teachers' attitudes toward and readiness to adopt AI (Mah & Groß, 2024), and the importance of professional development tailored to the specific needs of boarding schools and religious education settings (Fathullah et al., 2023). Although these studies provide useful insights, they differ in their research focus, outcome variables, and educational contexts. Their findings point to the need for a more integrated examination of how organizational support and teachers' individual capabilities relate to the use of AI in education, rather than addressing technology integration, AI readiness, and context-specific professional development as separate issues.

This study draws on four related concepts. The first is digital leadership in education, which involves the skills and strategies needed to support meaningful technology adoption, including establishing a digital vision, fostering a digital learning culture, and promoting systemic improvement (Karakose et al., 2024). The second is teachers' technological competence, understood as the knowledge, skills, and professional attitudes required to design and deliver technology-based instruction effectively (Aydin et al., 2024; Rosodor & Putra, 2025; Rusmini & Alfiandi, 2025). The third concept, teacher efficacy, refers to teachers' confidence in their ability to provide quality digital instruction, including managing digital fatigue and regulating their emotions (Yang & Du, 2024). The fourth is AI-based learning, which uses algorithms to personalize learning, provide automated feedback, and inform instructional decisions through data analysis. Its implementation, however, continues to raise ethical and pedagogical concerns (Azizah et al., 2026; Fitriana et al., 2026; Mukhoiyaroh et al., 2025; Mustafa et al., 2024). Within this framework, school leadership and operational oversight help establish the organizational conditions and professional support teachers need to prepare for technology integration (Siagian et al., 2025).

The relationships among the study's main constructs are based on Bandura's Social Cognitive Theory, which explains human functioning through the reciprocal interaction of personal factors, environmental conditions, and behavior (Bandura, 1986). In this study, digital leadership represents the organizational environment that provides direction, resources, and support for AI integration, while technological competence reflects teachers' knowledge and skills in using technology. Teacher efficacy represents the personal belief that may connect these organizational and technological factors to instructional practice. Teachers who receive leadership support and have stronger technological competence may feel more confident in using AI for teaching. This confidence, in turn, may be associated with their engagement in AI-based learning. The proposed model thus explains how organizational support and individual capabilities relate to AI-based instructional practices through teacher efficacy.

The existing literature points to three related research gaps. At the theoretical level, previous studies have generally examined digital leadership, teachers' technological competence, and teacher efficacy separately rather than bringing them together in a single framework to explain AI-based learning (AlAjmi, 2022; Mah & Groß, 2024). Regarding the underlying mechanism, less attention has been paid to how leadership support and technological competence may translate into AI-based instructional practices through teacher efficacy. A contextual gap also remains. Research on AI in education has largely focused on higher education or technology adoption in general, while

empirical studies examining the combined roles of organizational and individual factors among schoolteachers, particularly across diverse educational management settings, remain relatively limited (Fathullah et al., 2023; Fitriana et al., 2026; Mustafa et al., 2024). This study addresses these gaps by examining the direct relationships of digital leadership and technological competence with AI-based learning, as well as the mediating role of teacher efficacy.

Building on the conceptual framework and research gaps identified in the literature, this study examines the relationships among digital leadership, teachers' technological competence, and AI-based learning, with teacher efficacy as a mediating variable. The study addresses seven research questions: (1) Does teacher efficacy mediate the relationship between digital leadership and AI-based learning? (2) Does teacher efficacy mediate the relationship between technological competence and AI-based learning? (3) Does digital leadership have a direct effect on AI-based learning? (4) Does teachers' technological competence affect AI-based learning? (5) How does digital leadership relate to teacher efficacy? (6) How does technological competence relate to teacher efficacy? and (7) To what extent does teacher efficacy affect AI-based learning? These questions are investigated through a quantitative survey using a cross-sectional design. Structural Equation Modeling (SEM) is used to examine the direct relationships among the constructs and the mediating role of teacher efficacy, as this method is suitable for analyzing relationships involving latent constructs (Alismaiel, 2021; Wu et al., 2024).

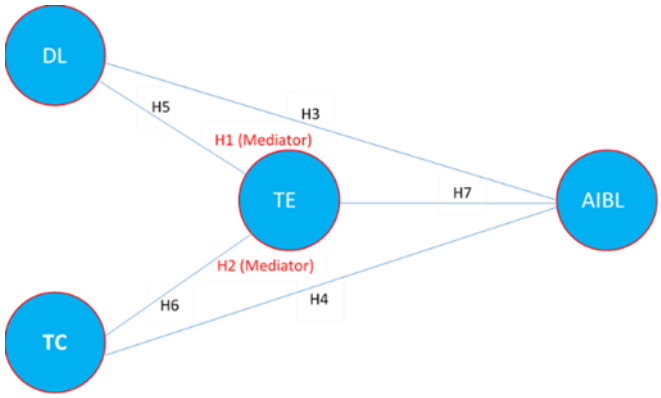


Figure 1. PLS-SEM Path Diagram
DL = Digital Leadership; TC = Technological Competence; TE = Teacher Efficacy; AIBL = AI-Based Learning

The novelty of this study lies in its examination of how digital leadership, technological competence, and teacher efficacy work together in relation to AI-based learning. Rather than treating AI adoption, technology readiness, and teachers' perceptions as separate outcomes, the study positions teacher efficacy as a mediating factor that may explain how organizational support and teachers' technological capabilities relate to AI-based instructional practices. The model also examines the direct relationships of digital leadership and technological competence with AI-based learning. Using survey data from 222 teachers drawn from a population of 500 teachers, the study tests this integrated mediation framework to clarify how leadership and technological competence may be associated with AI-based learning, both directly and indirectly through teachers' efficacy beliefs.

METHOD

This study uses a quantitative associative approach with an explanatory design and a cross-sectional survey to examine the relationships among digital leadership, technological competence, teacher efficacy, and the effectiveness of AI-based learning. It also examines the mediating role of teacher efficacy within the proposed conceptual model. Cross-sectional surveys are commonly used in educational research to investigate relationships between psychosocial constructs and learning outcomes at a specific point in time. This design offers practical advantages in terms of cost and respondent reach and has been applied in studies using Structural Equation Modeling (SEM) (Liang

et al., 2025). Primary data were collected through a structured questionnaire covering knowledge, attitudes, and behaviors related to AI in educational settings. This approach is consistent with recent methodological work on AI literacy and readiness in academic environments (Busch et al., 2024).

The study population consisted of 500 teachers, from which 222 active teachers participated in the survey. Data were collected using a closed-ended questionnaire with a Likert-type scale. The instrument measured the latent constructs through a reflective measurement model, in accordance with the study's objectives of testing hypotheses and examining mediation effects. SEM was selected because it allows relationships among multiple constructs to be analyzed simultaneously, including both direct and indirect effects within a single theoretical framework (Ahmmed et al., 2024). The mediating effects were assessed using non-parametric bootstrapping with bias-corrected confidence intervals, following recommendations for current PLS-SEM practices (Cheah et al., 2021).

The questionnaire was developed through several steps, beginning with construct identification, followed by item formulation and content validation. For instruments originally developed in languages other than Indonesian, cross-cultural adaptation was conducted in accordance with international standards. The process included preparation, forward translation, synthesis, back-translation, expert panel review, field testing, and finalization (Cruchinho et al., 2024). These procedures followed established guidance on translator involvement, consensus building, and systematic documentation to maintain equivalence of meaning and ensure that questionnaire items were clear to respondents (Coskun Benlidayi & Gupta, 2024). Initial instrument validation addressed content validity, construct validity, and internal reliability, consistent with recommended practices for developing instruments in educational technology research (Rhayha & Alaoui Ismaili, 2024).

Respondents were eligible to participate if they (1) were actively teaching in formal educational institutions, (2) had knowledge of or experience with AI-based instructional technologies, and (3) voluntarily agreed to participate after providing informed consent (Hochberg & Eakin, 2024). Teachers who were no longer actively teaching, submitted incomplete questionnaires, or showed repetitive extreme response patterns that could indicate inconsistent answers were excluded from the analysis (Jiang et al., 2025). These criteria were applied to maintain the quality and reliability of the data used in the analysis.

The sample size was determined with reference to current guidelines for Structural Equation Modeling (SEM). Rather than relying solely on the traditional ten-times rule, sample size considerations took into account model complexity, the number of indicators, and the expected effect size (J. F. Hair et al., 2021). In PLS-SEM, these considerations are particularly relevant because the method places greater emphasis on predictive performance and can accommodate moderate sample sizes under appropriate conditions (J. Hair & Alamer, 2022).

Data were collected using a questionnaire with a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The items were developed based on established theories and previous studies addressing digital leadership, technological competence, teacher efficacy, and AI-based learning (Ifenthaler & Yau, 2022). The questionnaire comprised five sections: (1) respondent demographics, (2) digital leadership, covering visionary, instructional, and innovative leadership, (3) technological competence, focusing on knowledge and pedagogical application, (4) teacher efficacy, covering instructional efficacy and efficacy in engaging students, and (5) AI-based learning, focusing on the adaptation of teaching practices through AI.

The measurement model was assessed before the structural model was examined. Since the study used Partial Least Squares Structural Equation Modeling (PLS-SEM), the assessment covered indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Indicator reliability was examined using standardized outer loadings. Internal consistency was evaluated through Cronbach's Alpha, Composite Reliability (CR), and Omega coefficients. Convergent validity was assessed using Average Variance Extracted (AVE), following established

PLS-SEM guidelines (J. Hair & Alamer, 2022; Henseler et al., 2015; Nemt-allah et al., 2024; Stefana et al., 2025). Discriminant validity was examined using the Heterotrait–Monotrait (HTMT) ratio, in accordance with established criteria for variance-based structural equation modeling (Henseler et al., 2015; Roemer et al., 2021). These assessments were conducted for all four reflective constructs in the model: Digital Leadership (DL), Technological Competence (TC), Teacher Efficacy (TE), and AI-Based Learning (AIBL).

After assessing the measurement model, the structural model was examined to test the hypothesized relationships among the latent constructs. The assessment covered collinearity diagnostics using the Variance Inflation Factor (VIF), the coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and standardized path coefficients (β). R^2 indicated how much variance in the endogenous constructs could be explained by their predictors, while f^2 measured the contribution of each exogenous construct to the explained variance. Predictive relevance was assessed using Q^2, and the Standardized Root Mean Square Residual (SRMR) was used to assess model fit, in line with PLS-SEM reporting guidelines (J. Hair & Alamer, 2022; Roemer et al., 2021). The analysis focused primarily on the model's explanatory and predictive performance rather than on global fit indices commonly associated with covariance-based structural equation modeling.

The hypothesized direct and indirect effects were tested using non-parametric bootstrapping with at least 5,000 resamples, following recommended PLS-SEM procedures (Cheah et al., 2021). Statistical significance was evaluated using bootstrap-based t-values, p-values, and bias-corrected confidence intervals. The mediation analysis examined whether Digital Leadership and Technological Competence were indirectly related to AI-Based Learning through Teacher Efficacy. The Variance Accounted For (VAF) was also calculated to describe the proportion of the total effect explained by the mediating variable, following approaches commonly used in PLS-SEM mediation studies (Jin et al., 2023).

Potential common method bias was examined using Harman's single-factor approach. A first-factor variance below 50% was treated as an indication that common method bias was unlikely to dominate the dataset (Polas, 2025; Rivera, 2024). The analysis proceeded in two main stages: assessment of the reflective measurement model and evaluation of the structural model, followed by bootstrapping to test the proposed direct and indirect relationships. This procedure was used to examine construct reliability and validity, the model's explanatory and predictive performance, and the mediating role of Teacher Efficacy within the proposed PLS-SEM framework.

The individual teacher served as the unit of analysis in this study. The sampling frame consisted of 500 active teachers from madrasahs, selected through stratified random sampling. This method was used because the population varies across educational levels. Dividing the population into more homogeneous subgroups can improve the accuracy and reliability of estimates compared with simple random sampling (Etikan, 2017). Educational level was chosen as the basis for stratification, covering three groups: Madrasah Ibtidaiyah (MI, equivalent to elementary school), Madrasah Tsanawiyah (MTs, equivalent to junior secondary school), and Madrasah Aliyah (MA, equivalent to senior secondary school). These levels were considered relevant because teaching contexts, digital infrastructure, and access to technology-related training may vary across madrasahs, potentially affecting teachers' technological competence and efficacy.

The population consisted of 170 MI teachers, 200 MTs teachers, and 130 MA teachers (Table 1). The target sample of 222 teachers was distributed proportionally across the three strata using the formula $n_h = (N_h / N) \times n$ (Cochran, 1977). This allocation resulted in 75 teachers from MI, 89 from MTs, and 58 from MA. Within each stratum, teachers were selected randomly from the teacher roster using a random number generator. To account for potentially invalid responses, questionnaires were distributed to 250 teachers, approximately 12.6% more than the target sample. All 250 questionnaires were returned. The responses were screened for completion time, uniform response patterns (straight-lining), and duplicate records to identify potentially careless or meaningless responses (Curran, 2016; Leiner, 2019). The screening process led to the exclusion of 28 questionnaires (11.2%): six duplicate entries, nine responses completed in abnormally short

periods, eight with inconsistent or straight-lining patterns, four identified as multivariate outliers, and one incomplete response. The remaining 222 questionnaires (88.8%) were retained for analysis. Their distribution across the three strata is presented in Table 1.

Table 1. Population, Sample Allocation, and Valid Responses by Madrasah Level

Stratum (madrasah level)	Population (N_h)	% of population	Allocated sample (n_h)	Questionnaires returned	Excluded	Valid responses
Madrasah Ibtidaiyah (MI)	170	34.0	75	85	10	75
Madrasah Tsanawiyah (MTs)	200	40.0	89	100	11	89
Madrasah Aliyah (MA)	130	26.0	58	65	7	58
Total	500	100.0	222	250	28	222

Sample size determination followed current PLS-SEM guidelines, taking into account model complexity, the number of indicators, and the model's predictive requirements (J. Hair & Alamer, 2022; J. F. Hair et al., 2021). Based on the inverse square root method proposed by Kock and Hadaya (2018), a sample of 222 was sufficient to detect path coefficients of approximately 0.17 or higher at a 5% significance level and 80% statistical power (Kock & Hadaya, 2018). The observed path coefficients, ranging from 0.28 to 0.36, exceeded this threshold. The methodological approach also reflects current research on digital education and artificial intelligence by combining a theoretical foundation with quantitative evidence to examine the relationships of digital leadership and technological competence with AI-based learning, including the mediating role of teacher efficacy (Ifenthaler & Yau, 2022; Teo, 2021).

RESULT AND DISCUSSION

Result

A total of 250 questionnaires were returned. After data screening, 28 questionnaires (11.2%) were excluded because they failed to meet the data-quality criteria, including duplicate entries, unusually short response times, and inconsistent response patterns. The remaining 222 questionnaires (88.8%) were considered valid and retained for analysis. These valid responses accounted for 44.4% of the target population of 500 teachers. The two percentages reflect different measures: 88.8% is the proportion of returned questionnaires retained after screening, while 44.4% is the proportion of the target population represented by the valid responses.

The respondents consisted of 35% men and 65% women, with a mean age of 39.2 years (SD = 6.8) and an average teaching experience of 12.7 years. Most taught at the junior secondary level and worked in public schools. Approximately 60% had participated in training related to instructional technology or AI. Descriptive statistics for each indicator included the mean (M), standard deviation (SD), skewness, and kurtosis. All values were within the acceptable range for a normal distribution, indicating that the data were suitable for subsequent inferential analysis.

Measurement Model (Outer Model)

The measurement model covered four main constructs: Digital Leadership (DL), Technological Competence (TC), Teacher Efficacy (TE), and AI-Based Learning (AIBL). Internal consistency was assessed using Cronbach's Alpha (α), Composite Reliability (CR), and Omega (ω), while convergent validity was evaluated using the Average Variance Extracted (AVE). Standardized indicator loadings ranged from 0.82 to 0.91, reflecting strong indicator performance and convergent validity.

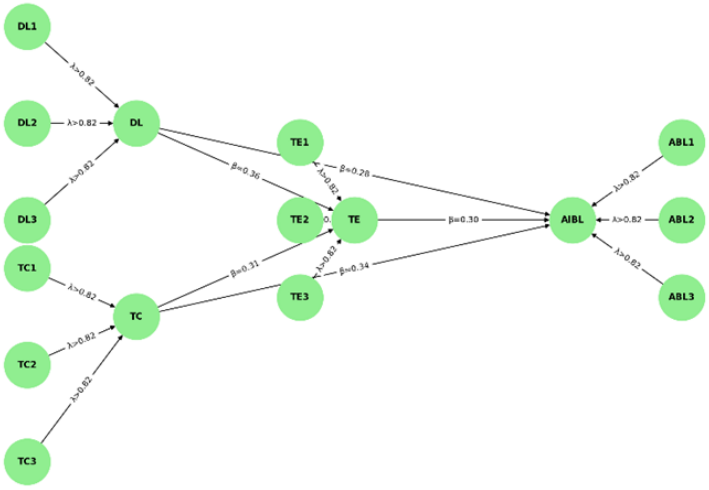


Figure 2. Model PLS-SEM: Outer dan Inner Loading

The visualization illustrates the relationships between latent constructs and their indicators (outer model), as well as the interrelations among constructs (inner model). All indicators demonstrated loadings greater than 0.82, and all structural paths between constructs were significant, with standardized beta coefficients (β) ranging from 0.28 to 0.36.

Discriminant Validity

Discriminant validity was assessed using the Heterotrait–Monotrait (HTMT) ratio and bootstrap confidence intervals. All HTMT and HTMT² values fell below 0.90, and the confidence intervals did not include 1, indicating that the constructs were empirically distinct. The Fornell–Larcker criterion also showed that the square root of the AVE for each construct exceeded its inter-construct correlations. Cross-loading analysis further confirmed that each indicator loaded more strongly on its designated construct than on the other constructs.

Bias Testing and Data Adequacy

The analysis of potential common method bias (CMB) revealed no serious issues, with the proportion of variance explained by the first factor at 32%, which is below the 50% threshold. Multicollinearity testing also indicated variance inflation factor (VIF) values < 3.3 across all constructs, suggesting no presence of high collinearity. Four outlier cases were removed based on Mahalanobis distance values, while missing data (1.6%) were addressed using mean replacement. These preprocessing procedures were conducted before structural model assessment.

Table 2. Structural Path Testing Results (Direct & Indirect Effects)

Relationship	Effect Type	β	t	p	CI 95%	VAF (%)
DL → AIBL	Direct	0.28	5.42	<0.001	0.19–0.36	–
TC → AIBL	Direct	0.34	6.31	<0.001	0.26–0.43	–
TE → AIBL	Direct	0.30	5.87	<0.001	0.21–0.39	–
DL → TE	Direct	0.36	7.22	<0.001	0.28–0.45	–
TC → TE	Direct	0.31	6.03	<0.001	0.22–0.40	–
DL → TE → AIBL	Indirect (Mediation)	0.108	4.17	<0.001	0.06–0.16	27.8%
TC → TE → AIBL	Indirect (Mediation)	0.093	3.92	<0.001	0.05–0.14	21.5%

Overall, Technological Competence was the strongest direct predictor of AI-Based Learning (β = 0.34), followed by Teacher Efficacy (β = 0.30) and Digital Leadership (β = 0.28). Digital Leadership exerted the strongest influence on Teacher Efficacy (β = 0.36), slightly exceeding the effect of Technological Competence (β = 0.31). Both indirect effects through Teacher Efficacy were significant, with a larger mediated contribution for Digital Leadership (β = 0.108; VAF = 27.8%) than for Technological Competence (β = 0.093; VAF = 21.5%). Because the direct effects remained significant and both VAF values indicated partial mediation, Teacher Efficacy accounted for part, but not all, of the relationships between the two antecedents and AI-Based Learning.

Table 3. Structural Model Path Estimates

Hypothesis	Path	β	SE	t-value	p-value	CI 95%	Remark
H3	DL → AIBL	0.28	0.05	5.42	<0.001	0.19–0.36	Significant
H4	TC → AIBL	0.34	0.05	6.31	<0.001	0.26–0.43	Significant
H5	TE → AIBL	0.30	0.04	5.87	<0.001	0.21–0.39	Significant
H6	DL → TE	0.36	0.04	7.22	<0.001	0.28–0.45	Significant
H7	TC → TE	0.31	0.05	6.03	<0.001	0.22–0.40	Significant
H1	DL → TE → AIBL	0.108	0.03	4.17	<0.001	0.06–0.16	Partial Mediation
H2	TC → TE → AIBL	0.093	0.02	3.92	<0.001	0.05–0.14	Partial Mediation

This table presents the structural path estimates within the PLS-SEM model. All paths yielded high t-values and p-values less than 0.001, indicating that all relationships among the constructs are statistically significant. The mediation paths through Teacher Efficacy were also found to be significant, further supporting its role as a partial mediator.

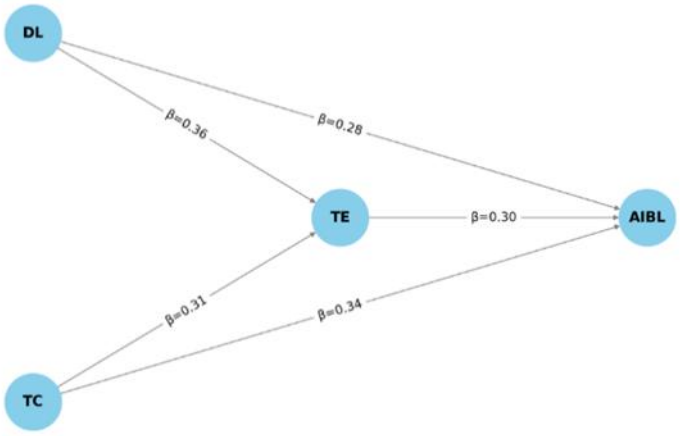


Figure 3. Diagram Jalur PLS-SEM

The hypothesized relationships are interpreted using the standardized path coefficients, bootstrapped t-values, p-values, and confidence intervals reported in the structural model results. Separate scatterplots are therefore omitted because they do not provide additional information beyond the PLS-SEM estimates.

Model Fit

The Standardized Root Mean Square Residual (SRMR) value was 0.046, below the threshold of 0.08. The PLSpredict results also indicated that the model demonstrated stronger predictive performance than a standard linear regression model.

Discussion

This study is theoretically informed by Social Cognitive Theory, which explains human functioning through the reciprocal interaction of personal factors, behavior, and environmental conditions (Bandura, 1986, 1997). Within this perspective, teacher efficacy represents a key personal belief that shapes whether teachers feel capable of translating available resources and professional knowledge into instructional action. Digital leadership can be understood as an organizational and environmental condition that provides direction, support, and opportunities for technology integration, while technological competence represents an individual capability that may enable teachers to use AI-supported tools in pedagogically meaningful ways. Bringing these dimensions together, the present study applies Social Cognitive Theory to examine teacher efficacy as a mediating mechanism linking digital leadership and technological competence with AI-Based Learning. The theoretical contribution lies not in treating leadership, competence, and efficacy as separate predictors, but in testing their relationships within one explanatory model of AI-based instructional practice. This framing provides a basis for interpreting the direct and indirect

relationships reported below, while recognizing that the cross-sectional design supports interpretation of associations rather than definitive causal conclusions.

The findings provide empirical support for an integrated explanation of AI-Based Learning in which organizational conditions, teachers' technological capabilities, and psychological factors operate simultaneously. The positive association between Digital Leadership and AI-Based Learning suggests that leadership may contribute to the creation of an organizational environment in which teachers are encouraged and supported to integrate AI into instructional practices. This interpretation is consistent with research emphasizing the importance of digital vision, organizational culture, and leadership support in facilitating technology integration and improving educational service quality (Fitriana et al., 2026; Karakose et al., 2024; Riski et al., 2024). Rather than functioning only as an administrative resource, digital leadership can provide direction and institutional support that enables teachers to translate technological opportunities into instructional practices.

The significant relationship between Technological Competence and AI-Based Learning further indicates that teachers' technological and pedagogical capabilities are relevant to the effective use of AI-supported instruction. This interpretation is consistent with evidence concerning the importance of technological and pedagogical knowledge in designing learning activities involving automated feedback, personalization, and other technology-supported instructional processes (Aydin et al., 2024; Chifla-Villón et al., 2025; Dirman et al., 2025; Sumpana & Bahri, 2026). The finding therefore extends the discussion of AI adoption beyond access to technology by emphasizing the capacity of teachers to use technological resources in pedagogically meaningful ways.

The role of Teacher Efficacy provides an additional psychological explanation for the relationships observed in the model. The significant association between Teacher Efficacy and AI-Based Learning is consistent with research linking teachers' efficacy beliefs with instructional design, emotional regulation, resilience, and adaptation to emerging technologies (Akram et al., 2022; Yang & Du, 2024). More importantly, the mediation findings suggest that organizational leadership and technological competence may operate partly through teachers' perceptions of their capability to manage and implement technology-supported instruction. This interpretation is consistent with previous evidence positioning teacher efficacy as an important bridge between technological-pedagogical competence and instructional implementation (Zeng et al., 2022), and with research indicating that leadership effects on educational outcomes may operate through psychosocial mechanisms such as school climate and teacher efficacy (Shao et al., 2025).

Taken together, the findings extend previous research by integrating organizational and individual dimensions within a single explanatory framework for AI-Based Learning. The model suggests that effective AI integration is not solely a function of technological competence or institutional leadership in isolation; rather, these conditions are interconnected with teachers' psychological readiness to translate technological resources and organizational support into instructional practice. This perspective is particularly relevant in educational contexts characterized by differences in infrastructure, professional development opportunities, and digital readiness (Okunlola & Naicker, 2025; Raptis et al., 2024). At the same time, the findings should be interpreted within the contextual and methodological boundaries of the study, including its cross-sectional design, single-source data, and specific educational setting.

Theoretically**,** these findings support an integrative framework that positions digital leadership as a catalyst for creating innovative learning environments. Leadership that emphasizes a strong digital vision, the cultivation of school culture, and technological transformation is believed to enhance teachers' confidence in integrating AI into instructional practices. Prior literature also highlights the importance of human-centered leadership competencies to ensure that digital innovation enhances the quality of learning rather than merely promoting tool adoption (Karakose et al., 2024; López-Figueroa et al., 2024). The contribution of transformational leadership in fostering a culture of quality further explains how institutional support can strengthen

both teacher efficacy and the effectiveness of technology implementation (Hadiati et al., 2025; Isa et al., 2024). The findings related to teachers' technological competence are also consistent with the literature on digital capacity assessment. The validity of instruments such as DigCompEdu and TPACK demonstrates that both technological and pedagogical skills are prerequisites for designing learning activities that leverage AI, particularly in delivering automated feedback and personalizing instruction (Aydin et al., 2024; Chifla-Villón et al., 2025). Within a psychological framework, the significant role of Teacher Efficacy (TE) in relation to AI-Based Learning (AIBL), as well as its mediating function, can be explained by its association with instructional design, digital emotion regulation, and teacher resilience when adapting to emerging technologies (Akram et al., 2022; Yang & Du, 2024).

Compared to previous studies, this research expands the empirical evidence on the relationship between digital leadership and teachers' technology integration, particularly in the post-pandemic context and the era of digital disruption. It focuses on AI-Based Learning (AIBL) as an instructional output, rather than merely measuring perceptions or intentions, thereby offering a more operational perspective (AlAjmi, 2022). Simultaneously, the rise in AIEd publications underscores the importance of ethical and pedagogical readiness, and this study contributes by linking readiness variables to actual classroom outcomes (Bond et al., 2024; Garzón et al., 2025). The relevance of teacher efficacy as a key factor in implementing Generative AI (GenAI) is also reinforced by these findings (Alfarwan, 2025). From a psychological perspective, meta-analyses have shown a strong relationship between teacher efficacy and technological-pedagogical knowledge (TPACK), supporting the role of efficacy as a bridge between competence and instructional implementation (Zeng et al., 2022). The partial mediation findings in this study also align with other research indicating that leadership does not always directly influence learning outcomes, but often operates through psychosocial factors such as school climate or teacher efficacy (Shao et al., 2025). Studies on innovative leadership further emphasize the importance of adaptive approaches to digital transformation (Witthöft et al., 2025).

Several cross-context studies, particularly in the Global South, highlight variations in digital readiness due to disparities in infrastructure and competencies. The findings of this study—emphasizing the combined roles of leadership and competence, with efficacy as a mediator—are highly relevant for context-sensitive intervention strategies (Okunlola & Naicker, 2025; Raptis et al., 2024). Moreover, the development of AI literacy frameworks and their assessment tools indicates that strengthening teacher efficacy must be supported by comprehensive literacy evaluations, including ethical dimensions and bias awareness (Lintner, 2024). The consistency of structural paths in this model also aligns with existing literature linking teacher readiness and leadership support to AI adoption (Ahyani et al., 2024; Amalia, 2026; Cahyono et al., 2025; Pambudi et al., 2024). However, several nuances warrant attention. Not all forms of leadership support have a direct impact on learning outcomes, as the strength of influence depends greatly on the quality of interaction and organizational context (Jensen et al., 2025). Additionally, methodological and theoretical variations across AIEd studies complicate cross-study generalizations, making standardized reporting—as exemplified in this study—essential (Bond et al., 2024; Demir & Uşak, 2025).

This article offers both theoretical and practical contributions. Theoretically, the proposed model integrates four key constructs within a mediation framework that bridges organizational and individual dimensions toward instructional outcomes. It extends the literature's typical focus on perceptions to emphasize actual outcomes in AI-based instructional practice. Practically, the findings provide a foundation for targeted interventions: strengthening digital leadership to manage change, developing teacher competence using validated instruments, and enhancing teacher efficacy through reflective approaches such as coaching and lesson study. These implications align with existing literature that calls for teacher policies and training programs that are technically sound, ethically grounded, and pedagogically balanced (Alfarwan, 2025; Aydin et al., 2024; Garzón et al., 2025). Furthermore, the established link between principal supervision and teacher

professionalism reinforces the rationale for considering efficacy as a mediating pathway in AI adoption (Siagian et al., 2025). Methodologically, the use of PLS-SEM is appropriate for analyzing complex models with multiple constructs, allowing for the estimation of both direct and mediated effects, as well as model quality validation through indicators such as SRMR, R^2, Q^2, and f^2 (Edeh et al., 2023). The assessment of validity and control for common method bias strengthens the causal inferences drawn. The finding of partial mediation also supports the view that the effect of leadership on learning is not singular, but is shaped by working climate and teachers' psychological conditions (Shao et al., 2025).

Several limitations should be acknowledged. First, the cross-sectional design restricts temporal generalizability; longitudinal studies are needed to examine changes over time. Second, the use of single-source data is susceptible to bias, despite statistical testing; combining it with observational data or learning artifacts could enhance external validity. Third, the measurement of AI-Based Learning (AIBL) did not explicitly distinguish between Generative AI (GenAI) and non-generative AI, despite the fact that each presents distinct challenges (Lin & Tan, 2025). Fourth, the geographic context and educational level of the respondents limit generalizability, suggesting that replication in regions with high digital disparity would further strengthen the findings (Okunlola & Naicker, 2025).

The practical and policy implications of this study include: (1) strengthening AI-based digital leadership training for school principals, with a focus on governance and ethical considerations; (2) enhancing teacher professional development through programs that integrate AI literacy and reflective practice to boost efficacy; (3) utilizing validated measurement instruments to assess competence and AI readiness; (4) prioritizing support for contexts with significant digital disparities through multi-layered strategies; and (5) advancing future research agendas involving multilevel-SEM analyses, intervention experiments, and cross-cultural replications to enrich multilevel understanding (Bond et al., 2024). From a technology adoption perspective, positioning teacher efficacy as a central mediating point aligns with the AIEd roadmap, which emphasizes personalized learning, automated feedback, and the importance of accountability and ethics. Policies that promote digital leadership and strengthen technological competence as mechanisms to enhance teacher efficacy represent an evidence-based and contextually relevant approach. In practice, structured digital literacy training, supported by strong leadership, can significantly improve teachers' readiness to adopt instructional technologies, including AI (Fathullah et al., 2023).

CONCLUSION

The results show that Digital Leadership, Technological Competence, and Teacher Efficacy are positively associated with AI-Based Learning. Technological Competence demonstrates the strongest direct relationship with AI-Based Learning ($\beta = 0.34$), whereas Digital Leadership has the strongest relationship with Teacher Efficacy ($\beta = 0.36$). Teacher Efficacy is also positively associated with AI-Based Learning ($\beta = 0.30$) and partially mediates the relationships between Digital Leadership and AI-Based Learning and between Technological Competence and AI-Based Learning. Taken together, these findings indicate that AI-based instructional practice is associated with both teachers' technological capabilities and the organizational conditions that support their work.

Theoretically, this study contributes an integrated mediation framework grounded in Social Cognitive Theory by connecting organizational conditions, individual technological capabilities, efficacy beliefs, and AI-Based Learning within a single explanatory model. The partial mediation results indicate that Teacher Efficacy is an important, but not exclusive, pathway through which Digital Leadership and Technological Competence are associated with AI-Based Learning. By retaining both direct and indirect relationships, the model offers a differentiated account of how environmental support and personal capabilities may relate to teachers' AI-based instructional practices.

For school leaders and education managers, the findings point to complementary priorities: establish a clear and responsible digital vision; provide sustained professional development in technological and pedagogical competence; and create opportunities for teachers to build efficacy through coaching, peer collaboration, and reflective practice. Institutional support should also include appropriate infrastructure, access to relevant tools, clear guidance on ethical AI use, data protection, and equitable access to digital resources. Future research could use longitudinal, intervention-based, or multilevel designs; incorporate objective indicators such as learning artifacts or performance data; distinguish generative from non-generative AI; and replicate the model across school types and cultural settings.

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