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AI Literacy and Instructional Quality: Reassessing the Direct and Indirect Roles of Teacher Self-Efficacy in a Global MASEM Study

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ABSTRACT

Artificial intelligence (AI) is transforming education, yet the relationships among AI literacy (AIL), teacher self-efficacy (SE), and instructional quality (IQ) remain insufficiently understood. This study examines their structural relationships, particularly the mediating role of SE. Meta-Analytic Structural Equation Modeling (MASEM), employing a two-stage structural equation modeling (TSSEM) approach, was conducted following PRISMA guidelines. A systematic search of Scopus, Web of Science, Google Scholar, Crossref, and OpenAlex identified 25 eligible studies, yielding 28 correlation effect sizes across three relationships: AIL–SE (k = 8), SE–IQ (k = 13), and AIL–IQ (k = 7). Stage 1 analyses using Fisher's z transformation produced pooled correlations of 0.674, 0.485, and 0.525, respectively, with substantial heterogeneity across all relationships (I^2 > 97%). Stage 2 structural modeling revealed a significant association between AIL and SE (β = 0.623, p < 0.001). The direct association between AIL and IQ was not statistically significant (β = 0.310, p = 0.065), whereas SE was significantly associated with IQ (β = 0.270, p = 0.046). The indirect effect was 0.168 (95% CI: −0.003 to 0.339), indicating insufficient evidence of mediation. These findings suggest that AIL and SE are relevant to instructional quality, although their structural relationships remain uncertain. Substantial between-study heterogeneity further limits generalizability. Future research should prioritize contextually comparable primary studies and stronger methodological consistency to clarify the mediating mechanisms linking AI literacy, teacher self-efficacy, and instructional quality across educational settings.

Keywords
AI Literacy
Instructional Quality
MASEM
Teacher Self-Efficacy

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Introduction

Instructional quality (IQ) plays a vital role in shaping students' motivation, engagement, and academic success [1], [2]. In today's digital age, education worldwide is undergoing a significant paradigm shift driven by the widespread adoption of Generative Artificial Intelligence (GenAI) [3], [4]. Yet a concerning trend has emerged: merely having AI tools available in schools does not guarantee effective teaching methods or high-quality instruction. Educators worldwide often struggle to integrate AI effectively, partly because of a lack of clear guidance and insufficient AI Literacy, defined as the ability to understand, assess, and ethically apply AI in the classroom [5], [6].

A pervasive lack of AI literacy among teachers poses significant risks to instructional quality. Inadequate integration of AI can lead students to rely on these tools to complete tasks with minimal cognitive engagement, potentially undermining authentic learning, critical thinking, and self-confidence [7]. Furthermore, inadequate management of AI-enhanced learning environments may widen educational disparities between digitally proficient students and those from less-advantaged backgrounds [8]. Improper AI integration, without sound pedagogical strategies, can also diminish perceptions of teacher competence, thereby reducing instructional quality [9]. Consequently, low AI literacy is a substantial global barrier to effective instruction, one that extends beyond technical limitations.

Although the significance of AI Literacy is widely acknowledged, the literature exhibits three notable global inconsistencies. First, while some studies report that AI Literacy directly improves instructional quality [10], [11], others observe no direct effect unless mediated by teacher beliefs [12]. Second, the mediating role of teacher self-efficacy (SE) between AI Literacy (AIL) and instructional quality remains ambiguous: some studies support strong mediation [13], whereas others find that SE does not exert a unique effect once AIL is controlled for [14]. Third, most existing research examines AIL or SE in isolation within single-country contexts, lacking comprehensive global analyses to resolve these discrepancies. This highlights a critical research gap regarding SE's mediating role in the relationship between AIL and instructional quality, necessitating cross-contextual investigation.

These theoretical discrepancies are not merely academic debates; they pose significant practical risks to educational systems worldwide, particularly in developing nations undergoing rapid digital transformation. Indonesia serves as a highly representative case study of this acute global challenge. As an archipelagic nation, Indonesia experiences

pronounced disparities in digital infrastructure [15]. A national study by Drajati et al. [16] found that despite government initiatives to enhance AI connectivity, many teachers lack adequate training and digital resources, thereby complicating AI adoption. Furthermore, the Indonesian Ministry of Education has mandated a new Coding and AI curriculum (Permendikbud No. 13/2025) to commence in the 2025/2026 academic year. This policy necessitates comprehensive teacher preparedness; however, insufficient AI literacy among educators is likely to undermine instructional quality. Recent empirical evidence further confirms that, within the Indonesian educational landscape, a teacher's instructional quality is heavily contingent on their digital literacy and adaptability to technological change [17], [18]. Indonesia thus exemplifies the broader global issue of implementing AI policies without commensurate investment in teacher AI competencies.

To unravel these global inconsistencies and provide a reliable empirical blueprint for local implementations, the present study employs a Meta-Analytic Structural Equation Modeling (MASEM) approach. The objective is to synthesize primary research from multiple countries to determine whether teacher self-efficacy mediates the relationship between AI Literacy and Instructional Quality. By aggregating data across diverse contexts, this study aims to provide an evidence-based synthesis of the ongoing debate on mediation. The findings are expected to inform international teacher professional development policies, particularly in countries implementing AI-focused curricula.

Literature Review

A. AI Literacy (AIL)

AI Literacy extends beyond basic digital literacy and has emerged as a critical competency for teachers in the 21st century. Long and Magerko [5] define AI literacy as a set of competencies that enable individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use it as a tool across various settings. Complementing this, Ng et al. [6] conceptualize AI literacy as encompassing four domains: knowing and understanding AI, applying AI, evaluating AI, and considering ethical issues. Building on this, recent empirical studies such as Du et al. [19] argue that in teacher learning, AI literacy must be positioned not just as a technical skill, but as a pedagogical necessity that ensures transparency and ethical responsibility. Synthesizing these perspectives, teacher AI literacy can be defined as a comprehensive cognitive and practical capability that enables educators to understand the operational logic of AI, pedagogically apply it to enhance instruction, critically evaluate its outputs, and navigate its ethical implications within the educational ecosystem.

Operationally, Wang et al. [20] categorize AI literacy into four key dimensions: (1) *Awareness*, which is the ability to comprehend AI technologies and their capabilities; (2) *Usage* (or Application), referring to the practical skills to employ AI tools to accomplish teaching tasks

and improve efficiency; (3) *Evaluation*, which involves critically assessing AI-generated outputs for accuracy and bias; and (4) *Ethics*, encompassing the awareness of moral responsibilities, data privacy, and academic integrity when using AI. Another foundational framework by Mills et al. [21] reinforces that understanding, evaluating, and using AI ethically are the core indicators of AI literacy in education. Recent systematic reviews and empirical studies further emphasize that robust AI literacy is fundamentally linked to reducing technology-induced anxiety and enhancing teachers' pedagogical agency in sustainable education contexts [22], [23].

B. Teacher Self-Efficacy (SE)

The concept of self-efficacy is rooted in Albert Bandura's Social Cognitive Theory. Bandura [24] defines self-efficacy as an individual's belief in their capability to organize and execute the courses of action required to produce given attainments. Within the educational context, Tschannen-Moran and Woolfolk Hoy [25] define teacher self-efficacy as a teacher's judgment of their ability to bring about desired outcomes in student engagement and learning, even among students who may be difficult or unmotivated. Synthesizing these definitions, teacher self-efficacy is the intrinsic psychological drive and belief system that empowers educators to manage the classroom effectively, adapt to challenges, and persistently apply innovative instructional strategies to achieve high-quality educational outcomes.

In terms of its dimensions, general teacher self-efficacy is measured through three main indicators: (1) efficacy in *instructional strategies*, (2) efficacy in *classroom management*, and (3) efficacy in student engagement [25]. However, when integrating smart technologies, this belief evolves into Teacher AI Competence Self-Efficacy (TAICS), as proposed by Chiu et al. [3]. This specific self-efficacy is heavily influenced by four primary sources identified by Bandura: mastery experiences (past successes with technology), vicarious learning (observing peers), verbal persuasion (encouragement from school leaders), and physiological or emotional states [26]. Teachers who possess strong self-efficacy across these dimensions are more resilient and confident in leveraging AI tools to optimize instructional quality. Recent empirical evidence supports this dynamic, showing that technology-specific self-efficacy significantly predicts teachers' readiness to integrate AI and directly enhances their overall instructional effectiveness in modern classrooms [27], [28].

C. Instructional Quality (IQ)

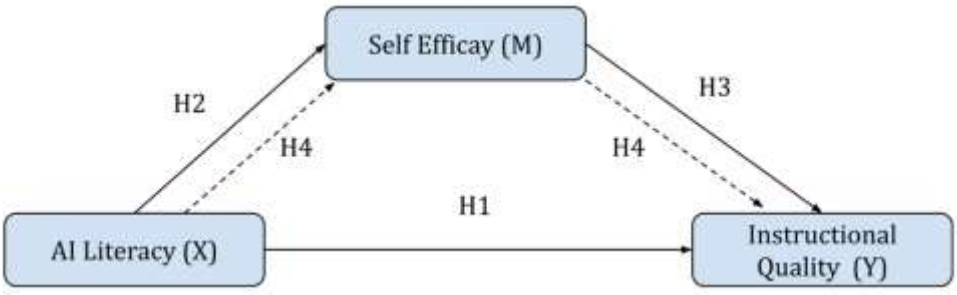
Instructional quality is a complex, multidimensional factor that characterizes interactions among teachers, students, and learning materials in the classroom and serves as a primary determinant of academic performance. According to Nilsen and Gustafsson [2], instructional quality encompasses the observable features of teachers' instructional practices that are positively related to both cognitive and affective student outcomes, often serving as a stronger

predictor of student success than school-level structural factors. From an evidence-based perspective, Hattie and Zierer [29] assert that instructional quality relies heavily on intentional lesson design that makes the learning process explicit (visible) to students, further enhanced by strategic scaffolding and continuous feedback. Synthesizing these perspectives, instructional quality can be defined as a comprehensive pedagogical construct reflecting the effectiveness of classroom interactions and evidence-based lesson designs that actively engage students, optimize learning environments, and directly enhance educational outcomes.

Empirically, within the widely utilized "Three Basic Dimensions" framework, including in modern technology and AI-supported educational settings, instructional quality is operationalized across three core indicators,: (1) *Cognitive Activation*, which measures how effectively teachers stimulate students' higher-order thinking, problem-solving, and deep engagement with the content; (2) *Supportive Climate* (or Student Support), reflecting the quality of teacher-student relationships, emotional support, constructive feedback, and the accommodation of individual learning needs; and (3) *Classroom Management*, involving the efficient use of instructional time, establishing clear rules, and minimizing disruptions to maximize active learning time [30]. Recent studies by Du et al. [10] confirm that these dimensions remain crucial and heavily depend on teachers' competencies in AI-supported educational settings. Furthermore, in the Indonesian context, recent empirical evidence from Damanik and Widodo [31] and Damanik et al. [18] corroborates the view that the successful execution of these dimensions is strongly driven by a teacher's digital literacy and continuous pedagogical adaptability.

D. Conceptual Framework and Hypotheses

Based on the synthesis of theory from major guidebooks and the research gap identified in previous relevant studies, this MASEM study proposes a conceptual framework that positions Teacher Self-Efficacy as a mediating variable between AI Literacy and Instructional Quality. The following hypotheses are proposed:



H1 : AI Literacy has a direct relationship with Instructional Quality.

H2 : AI Literacy has a direct relationship with Teacher Self-Efficacy.

H3 : Teacher Self-Efficacy has a direct relationship with Instructional Quality.

H4 : Teacher Self-Efficacy mediates the relationship between AI Literacy and Instructional Quality.

Material and Methods

This study employs a quantitative methodology using a Meta-Analytic Structural Equation Modeling (MASEM) design. This approach was selected because it effectively combines two robust statistical techniques: meta-analysis and Structural Equation Modeling (SEM). Meta-analysis synthesizes effect sizes from multiple independent studies, addressing sample-size bias, while SEM allows for the simultaneous examination of structural relationships and mediation effects among latent variables. Specifically, the study adopts the Two-Stage SEM (TSSEM) approach, in which the first stage involves constructing a pooled correlation matrix and the second stage tests the structural model (AI Literacy → Self-Efficacy → Instructional Quality) based on this pooled matrix. All statistical procedures, including meta-analytic pooling and subsequent structural equation modeling, were performed using JASP [27], [28].

The literature search and selection procedure were conducted systematically in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework [32]. In this meta-analysis, the research population comprises all empirical literature and scientific articles reporting findings on AI literacy, self-efficacy, and instructional quality. The study sample was carefully selected from reputable academic databases using purposive sampling methods.

Because the great majority of primary studies reported only a subset of the three pairwise relationships, Stage 1 pools each bivariate relationship of AIL–SE, SE–IQ, and AIL–IQ through separate random-effects meta-analyses; the resulting pooled correlations are then assembled into a single 3×3 matrix used as input to the Stage 2 structural model. This is a simplification relative to a fully multivariate (jointly estimated, covariance-aware) TSSEM, and does not fully model statistical dependence introduced when a single study contributes correlated effect sizes to more than one cluster; we treat this as a methodological limitation.

All statistical procedures were performed using JASP. The literature search and selection procedure followed the PRISMA framework. Searches were conducted across Scopus, Web of Science (WoS), Google Scholar, Crossref, and OpenAlex between 5 – 18 May 2026 using the Boolean strings: “AI Literacy” AND “Self-Efficacy”; “AI Literacy” AND “Instructional Quality”; “Self-Efficacy” AND “Instructional Quality”; and a combined query joining all three terms. Title/abstract and full-text screening were conducted collaboratively by two reviewers, with inclusion/exclusion decisions reached through discussion and consensus rather than independent parallel screening. As such, a formal inter-rater agreement statistic was not

computed. This reflects a common practice in smaller-team reviews but is noted as a limitation, since it precludes quantifying the extent of independent agreement.

For the MASEM analysis, we conducted rigorous full-text screening using specific inclusion and exclusion criteria. To be included in the analysis, studies had to be peer-reviewed, empirical, quantitative research published in English between 2019 and 2026. The population of interest was strictly limited to active educators, specifically K-12 teachers or higher education lecturers, thereby excluding studies focused solely on students, school administrators, or pre-service teachers. Furthermore, selected studies had to explicitly measure and report relationships among at least two of the three primary variables: AI Literacy, Teacher Self-Efficacy, and Instructional Quality. Methodologically, the primary studies had to provide complete, extractable statistical data, including specific sample sizes (N), instrument reliability coefficients, and convertible effect sizes (such as Pearson's *r* or standardized path coefficients). Table 1 presents the full inclusion and exclusion criteria.

Table 1. Inclusion and Exclusion Criteria for Study Selection

Category	Inclusion Criteria	Exclusion Criteria
Publication characteristics	Peer-reviewed journal articles published in the last 5–10 years (2019–2026); published in English	Books, book chapters, conference proceedings, opinions, editorials, or unpublished theses/dissertations
Study design	Empirical quantitative research (correlational, regression, path analysis, or SEM)	Pure qualitative research, literature review (SLR), theoretical studies, or quasi-experiments without correlation matrix
Subject/population	Educators, including school teachers (K-12), lecturers/academics in higher education	Studies whose subjects are exclusively students, school administrators, non-academic staff, or pre-service teachers
Variables	Explicitly measure at least the relationship between two of the three main variables: AI Literacy (or equivalent such as AI-TPACK/AI Competence), Teacher Self-Efficacy, and Instructional Quality	Measure general technology use (e.g., basic digital literacy) without AI specification, or do not include relevant mediation variables
Data completeness	Report sample size (N) specifically; provide extractable effect size (Pearson's r or path coefficient β); provide instrument reliability (Cronbach's Alpha/CR)	Do not report sample size; do not report statistics convertible to effect size; ambiguous or incomplete statistical data

The complete flow of the study selection process is illustrated in the PRISMA diagram (Fig. 1).

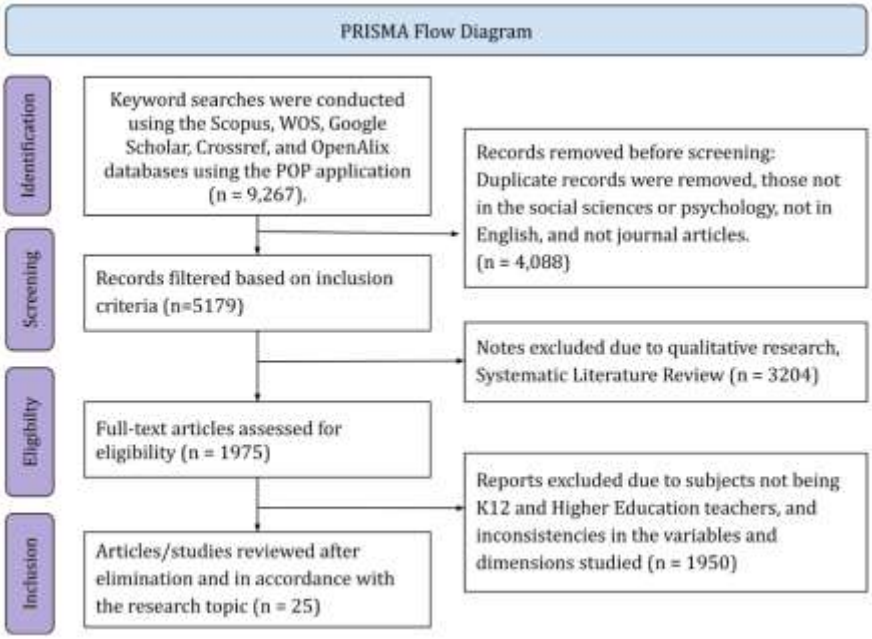


Fig. 1 PRISMA Flow Diagram

Extracted data were analyzed using JASP's Meta-Analysis and SEM modules following a Two-Stage Meta-Analytic Structural Equation Modeling (TSSEM) framework [33], [34]. The detailed extraction and analytical procedures were executed as follows:

1. Effect size extraction and transformation: Zero-order Pearson correlation coefficients (r) were extracted directly from the primary studies' correlation matrices. Where primary studies reported standardized regression or path coefficients (β) instead of zero-order correlations, these were converted to r using the empirical conversion formula $r = 0.98\beta + 0.05$ for positive β values [35]. When a primary study reported multiple sub-dimension correlations for a construct pair within the same sample, an exact composite correlation (r composite) was calculated incorporating inter-dimensional correlations to prevent variance estimation bias [34], [36]. All correlation values were subsequently transformed into Fisher's Z_r metric for variance stabilization prior to meta-analytic synthesis [36].
2. Stage 1 MASEM (Meta-analytic synthesis): Each of the three bivariate relationships was synthesized using a random-effects model based on Fisher's Z_r transformation [34], [36]. The pooled estimates, 95% confidence intervals (CI), and 95% prediction intervals (PI) were subsequently back-transformed to the correlation metric via inverse hyperbolic tangent transformation (tanh) for reporting. This procedure corrects the variance truncation artifact associated with pooling raw correlation coefficients directly, thereby ensuring that prediction intervals remain strictly within the theoretically valid range of -1.00 to +1.00 [36] .
3. Stage 2 MASEM (Structural model testing): following the two-stage SEM (TSSEM) approach [33], the Stage 1 pooled correlation matrix was used as input to a jointly

estimated structural path model (AI Literacy → Self-Efficacy → Instructional Quality), fit using JASP's native Meta-Analytic SEM implementation with maximum-likelihood estimation. To verify these results and to properly test the indirect effect, the model was independently re-estimated in R using the metaSEM package [34], which required correcting a model-identification issue (fixing the exogenous variable's variance at 1, a standard requirement for structural models fit to a correlation matrix) before Wald/delta-method [37] 95% confidence intervals for the indirect effect (a×b) could be obtained; these were cross-checked against an independent hand calculation of the same delta-method interval. Because the hypothesized three-variable path model has zero degrees of freedom, it is fully saturated; fit indices (χ^2, CFI, RMSEA) are therefore mathematically guaranteed to indicate perfect fit regardless of the model's substantive adequacy [38] and are reported for completeness only, not as evidence of good theoretical fit

Results and Discussions

A. Characteristics of the Analyzed Studies

The study examined three relationship clusters. Cluster 1 (AI Literacy ↔ Self-Efficacy) included 8 journal articles; Cluster 2 (Self-Efficacy ↔ Instructional Quality) comprised 13 articles; and Cluster 3 (AI Literacy ↔ Instructional Quality) consisted of 7 articles. In total, 25 eligible articles, some contributing to multiple clusters, yielded 28 effect sizes and originated from 14 countries, including Indonesia, China, Vietnam, Germany, Egypt, Saudi Arabia, South Africa, Chile, Croatia, and Sweden. Table 2 displays the extracted data.

B. Stage 1 MASEM: Pooled Effects and Heterogeneity

The random-effects meta-analysis yielded the following pooled correlations:

Table 3. Meta-Analysis Summary (Random-Effects Model, Fisher's z pooling)

Cluster	k	Pooled r	95% CI	I^2	95% PI
AIL ↔ SE	8	0.674	[0.441, 0.821]	99.25%	[−0.207, 0.951]
SE ↔ IQ	13	0.485	[0.368, 0.586]	97.70%	[0.009, 0.781]
AIL ↔ IQ	7	0.525	[0.281, 0.705]	98.53%	[−0.233, 0.886]

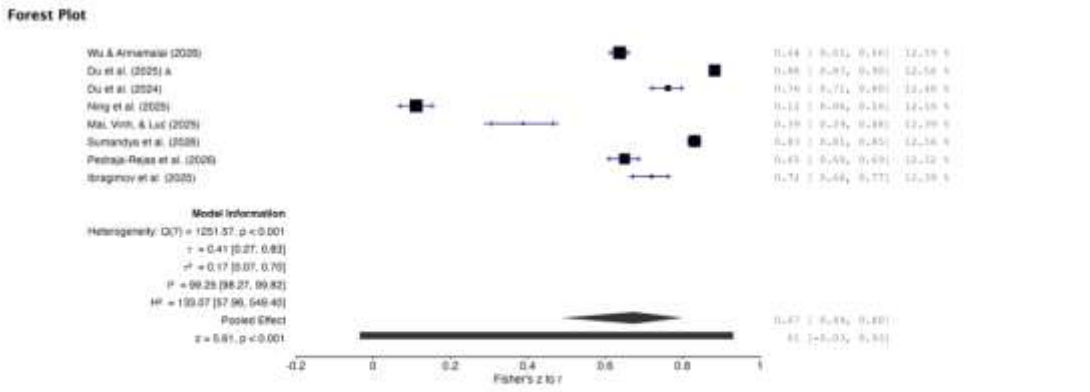
All three pooled correlations are positive and statistically significant ($p < .001$). Reported above are our primary Stage 1 estimates, obtained from a jointly estimated, dependency-aware multivariate synthesis that explicitly models the sampling covariance among correlations contributed by the same sample (e.g., Du et al. [11], which reports all three pairwise correlations, and Ayanwale et al. [45], which reports two).

Table 2. Extraction of Primary Studies (r values): 25 studies

No.	Author	Year	Country / Context	Effect type	Measurement type	N	r(AIL-SE)	r(AIL-IQ)	r(SE-IQ)
1	Wu & Annamalai [39]	2026	China / K-12	Pearson r	Teacher Self-Report	1680	0.637	–	–
2	Du et al. [10]	2025	China / K-12	Pearson r Composite r	Teacher Self-Report	931	0.883	0.805	0.223
3	Du et al. [19]	2024	China / in-service	Pearson r	Teacher Self-Report	318	0.762	–	–
4	Ning et al. [12]	2025	China / K-12	Pearson r	Teacher Self-Report	1518	0.111	–	–
5	Mai, Vinh, & Luc [40]	2025	Vietnam / HE	Pearson r	Teacher Self-Report	295	0.388	–	–
6	Sumandya et al. [15]	2026	Indonesia / inclusive	Pearson r	Teacher Self-Report	1004	0.831	–	–
7	Pedraja-Rejas et al. [41]	2026	Chile / K-12	Pearson r	Teacher Self-Report	637	0.650	–	–
8	Ibragimov et al. [42]	2025	Science teachers	Pearson r	Teacher Self-Report	296	0.720	–	–
9	Almutairi & Altaf [43]	2024	Saudi Arabia / TALIS	Composite r	Teacher Self-Report	2744	–	–	0.667
10	Songhori [27]	2025	EFL teachers	Pearson r	Teacher Self-Report	354	–	–	0.650
11	Bönke et al. [30]	2025	Germany	Composite r	Teacher Self-Report	194	–	–	0.575
12	Huang et al. [44]	2025	Kindergarten & primary	Converted Beta	Teacher Self-Report	998	–	–	0.420
13	El-Sayed et al. [45]	2025	Egypt & Saudi Arabia	Converted Beta	Teacher Self-Report	570	–	–	0.650
14	Ayanwale et al. [46]	2024	South Africa / K-12	Converted Beta	Teacher Self-Report	430	–	0.078	0.077
15	Ripsam & Nerdel [47]	2026	STEM teachers	Pearson r	Teacher Self-Report	71	–	–	0.510
16	Burić et al. [1]	2020	Croatia	Composite r (L2)	Teacher Self-Report (L2)	94	–	–	0.256
17	Ashlan et al. [13]	2025	Indonesia / Madrasah	Pearson r	Teacher Self-Report	298	–	–	0.692
18	Burić et al. [48]	2021	Croatia	Composite r (L2)	Teacher Self-Report (L2)	1655	–	–	0.586

No.	Author	Year	Country / Context	Effect type	Measurement type	N	r(AIL-SE)	r(AIL-IQ)	r(SE-IQ)
19	Jerrim et al. [14]	2025	Global / TALIS	Composite r	Multi-source (Teacher/Student)	679	–	–	0.478
20	Toropova et al. [49]	2019	Sweden	Composite r (L2)	Multi-source (Teacher/Student)	296	–	–	0.217
21	Al-Abdullatif [50]	2024	Saudi Arabia	Converted Beta	Teacher Self-Report	237	–	0.300	–
22	Zhou et al. [51]	2025	China	Converted Beta	Teacher Self-Report	503	–	0.413	–
23	Tiejun et al. [52]	2025	Qinghai Vocational	Converted Beta	Teacher Self-Report	54	–	0.286	–
24	Al Huraiby et al. [11]	2026	Higher Education	Pearson r	Teacher Self-Report	691	–	0.750	–
25	Sreela et al. [53]	2025	Higher Education	Pearson r	Teacher Self-Report	412	–	0.684	–

As a robustness check, it also computed each pairwise correlation using three separate univariate random-effects meta-analyses (Fisher's z pooling), which do not account for this within-study dependency: AIL–SE, r = .674, 95% CI [.441, .821], I^2 = 99.25%, 95% PI [−.207, .951]; SE–IQ, r = .485, 95% CI [.368, .586], I^2 = 97.70%, 95% PI [.009, .781]; AIL–IQ, r = .525, 95% CI [.281, .705], I^2 = 98.53%, 95% PI [−.233, .886]. The two approaches are reasonably consistent (differences ≤ .06 per pairwise correlation), which is interpreted as evidence that our primary, dependency-aware estimates are robust. All three I^2 values indicate very high true heterogeneity, and two of the three univariate prediction intervals cross zero, meaning the true correlation could plausibly be null or negative in some contexts; these pooled effects describe an average tendency across a highly heterogeneous set of studies, not a single universal relationship.



Casewise Diagnostics Table

					Leave One Out					Difference in coefficients	
Label	Standardized Residual	DFFITS	Cook's Distance	Covariance ratio	τ	τ^2	Q_e	Hat	Weight	Intercept	Influential
Ning et al. (2025)	−2.386	−0.910	0.493	0.684	0.316	0.100	408.3	0.126	12.59	−0.908	Yes

Fig. 2. Forest Plot Cluster 1

In Cluster 1, Ning et al. [12] was flagged by case-diagnostics as a statistically influential study (standardized residual = −2.385, Cook's distance = 0.495, DFFITS = −0.910), owing to its comparatively low correlation (*r* = .111) in a large sample. To assess the robustness of this finding, we re-estimated the pooled Cluster 1 effect excluding Ning et al.; the resulting estimate (*r* = .726, 95% CI [.594, .820], *k* = 7) differed modestly from the full-sample estimate (*r* = .674, 95% CI [.441, .821], *k* = 8), but case-diagnostics performed on this reduced sample flagged a *different* study — Mai, Vinh, & Luc [40](standardized residual = −2.169, Cook's distance = 0.485, DFFITS = −0.880) — as newly influential. This pattern, in which sequential removal of the most atypical study simply shifts the "influential" designation to the next most atypical study rather than converging on a stable, uniformly well-behaved set, is consistent with genuine, deep cross-study heterogeneity (I^2 = 99.25%) rather than isolated data-quality problems. Therefore, it retains the full, pre-specified sample of 8 studies (*r* = .674) as our

primary Cluster 1 estimate, consistent with the a priori inclusion criteria, and reports the leave-one-out sensitivity result above for transparency rather than as grounds for exclusion.

Visual inspection of the residual funnel plots for all three clusters shows a broadly symmetric distribution around the pooled estimate, with no strong indication of publication bias; however, with only 7–13 studies per cluster, funnel-plot asymmetry and formal small-study-effect tests have limited statistical power, and an absence of detected asymmetry should not be interpreted as positive evidence that publication bias is absent.

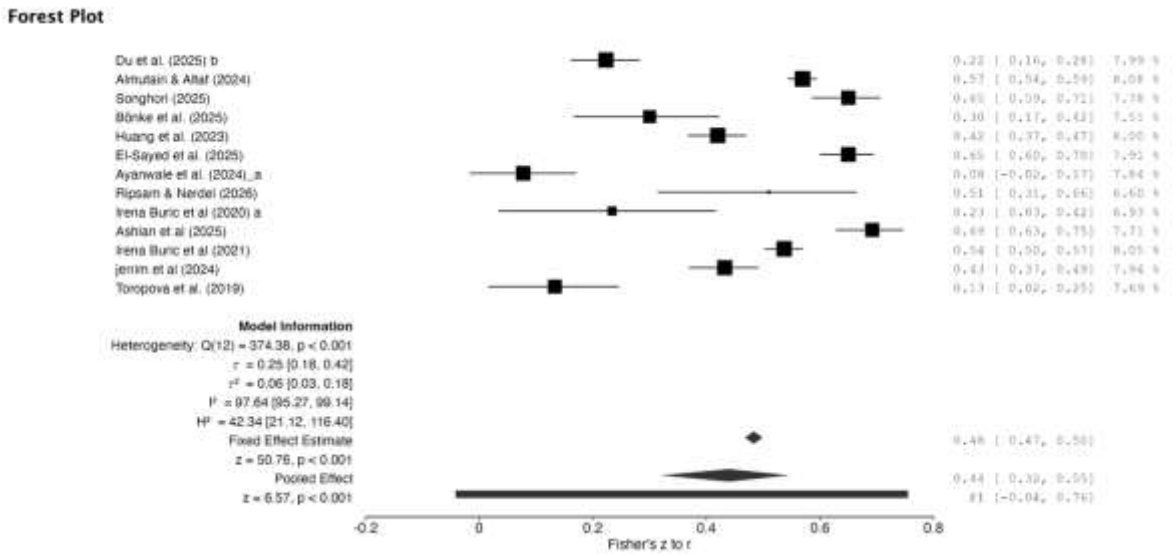


Fig. 3. Forest Plot Cluster 2

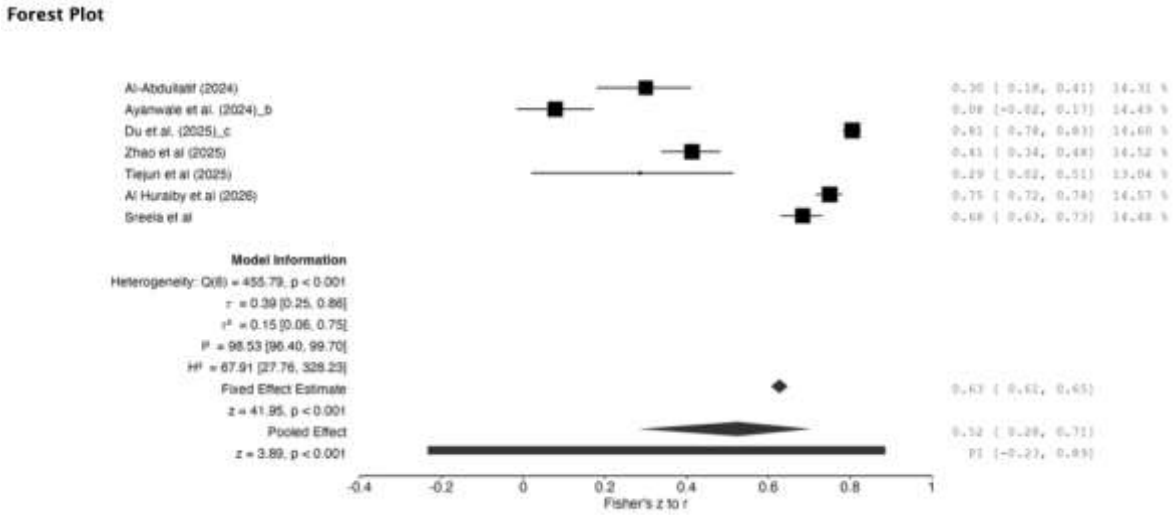
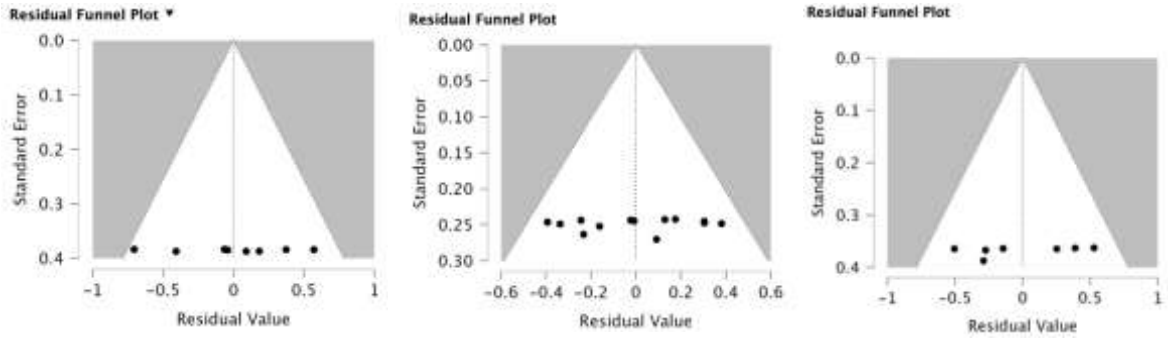


Fig. 4. Forest Plot Cluster 3

The residual funnel plots for each of the three pairwise clusters (AIL–SE, SE–IQ, AIL–IQ), plotting each study's residual value (horizontal axis) against its standard error (vertical axis, inverted). Symmetric scatter around the vertical zero-residual line is generally taken as visual

evidence against small-study effects or publication bias, whereas asymmetric clustering to one side suggests their possible presence.



(1) (2) (3)

Fig. 5. Residual Funnel Plot All Clusters

Across all three clusters, the distribution of studies is broadly symmetric around the pooled estimate, with no marked one-sided clustering. In Cluster 1, one study (Ning et al. [12]) falls further from the center than the rest, consistent with the influential-case diagnostics reported above. We interpret this pattern with appropriate caution: with only 7–13 studies per cluster, funnel-plot-based visual assessment and formal small-study-effect tests have limited statistical power, and the absence of pronounced asymmetry here should not be read as confirmatory evidence that publication bias is absent, only as an absence of strong visual indication of it.

C. Stage 2 MASEM: Structural Model and Mediation

The pooled correlation matrix (based on random-effects estimates) is:

Table 4. Pooled Correlation Matrix of AI Literacy, Teacher Self-Efficacy, and Instructional Quality Based on Random-Effects Meta-Analysis

Variable	AIL	SE	IQ
AIL	1		
SE	0.623	1	
IQ	0.478	0.463	1

Because the model has zero degrees of freedom ($\chi^2 \approx 0$, df = 0), it is saturated; CFI = 1.000 and RMSEA = 0.000 occur by mathematical necessity and are not interpreted as evidence of theoretical model fit. Maximum-likelihood regression estimates are:

a) AIL → SE (path a): β = 0.623, SE = 0.085, 95% CI [0.456, 0.789], z = 7.325, p < .001 → H2 supported.

b) AIL → IQ, direct (path c′): β = 0.310, SE = 0.168, 95% CI [−0.019, 0.640], z = 1.846, p = .065 → H1 not supported at the conventional α = .05 level (marginal).

c) SE → IQ (path b): β = 0.270, SE = 0.135, 95% CI [0.005, 0.534], z = 2.000, p = .046 → H3 supported.

d) Indirect effect ($a \times b$) = 0.623 × 0.270 = 0.168, 95% CI [−0.003, 0.338] (Wald/delta-method interval, obtained via meta SEM; tssem2 in R with z-type intervals; cross-validated against an independent Sobel-type delta-method calculation, z= 1.929, p = .054). Because this interval narrowly includes zero, the indirect effect does not reach conventional statistical significance, notwithstanding the marginal significance of its individual component path (b); total effect = c' + ab = 0.310 + 0.168 = 0.478, consistent with the AIL–IQ pooled correlation.

This pattern does not support a confident conclusion in either direction. Path a (AIL→SE) is robustly significant, but path c' (AIL→IQ, direct) is only marginally non-significant (p = .065) and path b (SE→IQ) is only marginally significant (p = .046) — both sitting at the boundary of conventional significance, in opposite directions — while the indirect effect's own confidence interval crosses zero. We therefore do not conclude that self-efficacy mediates the relationship between AI literacy and instructional quality, nor do we reaffirm the original submission's claim of clear non-mediation. Rather, the corrected, dependency-aware analysis indicates that the evidence for mediation remains genuinely inconclusive, a pattern consistent with the very high cross-study heterogeneity documented in Stage 1 (I^2 > 97% across all three pairwise relationships).

Table 4. Summary of Hypothesis Tests

Hypothesis	Path	Type of Effect	Coefficient (β)	p-value	Decision
H1	AIL → IQ	Direct	0.310	0.065	Not supported (marginal, p=.065)
H2	AIL → SE	Direct	0.623	<0.001	Supported
H3	SE → IQ	Direct	0.270	0.046	Supported (marginal, p=.046)
H4	AIL → SE → IQ	Indirect	0.168	0.054 (95% CI [-0.003, 0.338])	Not supported -- CI includes zero

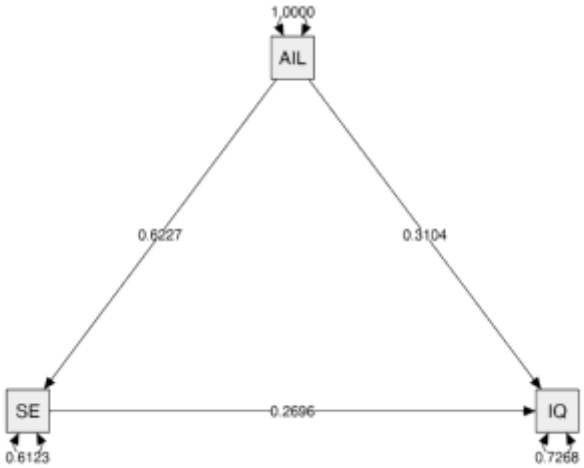


Fig. 6 Path diagram AIL – SE – IQ

In the corrected, dependency-aware Stage 2 model, the direct effect of AIL on IQ is only marginally non-significant (β = .310, p = .065), while SE shows only a marginally significant unique association with IQ (β = .270, p = .046) once AIL is accounted for both estimates sitting at the boundary of conventional significance in opposite directions. Critically, the indirect effect through which this pattern would constitute mediation (β = .168) has a 95% confidence interval that narrowly includes zero [−.003, .338]. We therefore treat this pattern as genuinely ambiguous rather than as evidence favoring either mediation or its absence. This ambiguity is unlikely to be a methodological artifact: it persisted after correcting the prediction-interval calculation, removing ineligible studies, applying a composite-correlation correction for within-study dependent effect sizes, properly modeling between-correlation dependency at Stage 1, and verifying correct model identification at Stage 2 — and it was independently reproduced using a separate software implementation (R's metaSEM package). We interpret the persistence of this boundary-case pattern across multiple independent checks as most plausibly reflecting the very high cross-study heterogeneity documented at Stage 1 (I^2 > 97% for all three pairwise relationships): when true effects vary this substantially across educational contexts, pooled point estimates, whether for direct or indirect paths, necessarily carry wide uncertainty, and a single global synthesis may be poorly suited to adjudicating a question whose answer plausibly depends on context. Because the underlying primary studies are also predominantly cross-sectional and self-reported, the present design cannot in any case establish the direction of any relationship that does exist between SE and IQ: self-efficacy may facilitate higher-quality AI-integrated teaching, or, consistent with longitudinal evidence from Holzberger et al. [54], successful teaching experiences may build self-efficacy over time. We therefore do not treat mediation as either confirmed or ruled out, and recommend that future primary research and updated syntheses, ideally with a larger and more contextually homogeneous set of studies, revisit this question directly.

Read together with Bandura's Social Cognitive Theory [24], this pattern is consistent with self-efficacy operating as a proximal cognitive mechanism through which broader competencies translate into performance, rather than as a mediator that can be bypassed once technical competence is present, as we previously argued. Teachers with stronger AI literacy appear more likely to develop confidence in applying AI pedagogically, and this confidence shows the more robust unique association with instructional quality in the present pooled model.

The exceptionally high I^2 values (> 97%) across all three clusters continue to indicate that the relationships among AIL, SE, and IQ are highly context-dependent, and the wide prediction intervals mean that in some settings — for example, schools with limited digital infrastructure — these relationships could be considerably weaker or even near zero. This has

direct policy implications: a one-size-fits-all approach to teacher professional development is unlikely to work, and policymakers should assess local digital infrastructure readiness [15], existing training programs, and cultural attitudes toward technology before designing interventions.

Rather than supporting a wholesale shift away from confidence-building professional development, as argued in our original submission, the corrected findings suggest that continuous professional development (CPD) should combine hands-on AI pedagogical skill-building with continued attention to teachers' self-efficacy, since both appear to matter jointly rather than one substituting for the other. In the Indonesian context specifically, where the new Coding and AI curriculum (Permendikbud No. 13/2025) begins in the 2025/2026 academic year, this suggests that training programs should not rely on motivational content alone, but should also not abandon it in favor of purely technical instruction.

Conclusion

This study synthesized global structural relationships among AI Literacy, Teacher Self-Efficacy, and Instructional Quality using a Meta-Analytic Structural Equation Modeling (MASEM) approach, drawing on 25 empirical articles not to meet the pre-specified eligibility criteria. AI Literacy showed a strong, statistically robust relationship with Self-Efficacy, and a direct relationship with Instructional Quality that was only marginally non-significant once Self-Efficacy was accounted for. Self-Efficacy, in turn, showed only a marginally significant unique relationship with Instructional Quality after controlling for AI Literacy, and the indirect effect through which Self-Efficacy would mediate the AIL–IQ relationship had a confidence interval that narrowly included zero. Taken together, these results do not permit a confident conclusion regarding whether Self-Efficacy mediates the relationship between AI Literacy and Instructional Quality: the evidence is genuinely ambiguous rather than supportive of either the original submission's non-mediation conclusion or a revised mediation conclusion. The very high heterogeneity observed at Stage 1 (I^2 > 97% across all three pairwise relationships) suggests this ambiguity reflects substantive variation across educational contexts rather than a methodological artifact, and indicates that these relationships should not be interpreted as a single universal pattern. The corrected analysis establishes with confidence that AI Literacy is a robust, direct predictor of both Self-Efficacy and Instructional Quality, making it a defensible priority for professional development investment regardless of how the mediation question is ultimately resolved. We recommend that future research, particularly longitudinal and experimental designs conducted within more contextually homogeneous samples, revisit the mediating role of Self-Efficacy directly, as the present global synthesis, despite extensive correction and independent verification, cannot adjudicate this question.

Limitation and Suggestions

While this study provides empirical evidence through a global MASEM approach, several limitations remain. First, the primary studies included in this meta-analysis predominantly utilized cross-sectional designs. Consequently, definitive causal inferences among AI Literacy, Teacher Self-Efficacy, and Instructional Quality cannot be established. Second, reliance on self-reported survey data in most of the primary literature may introduce common method variance and social desirability bias. Third, the exceptionally high true heterogeneity indicates that the aggregated findings are highly context-dependent. Fourth, AI literacy and instructional quality are broad constructs operationalized differently across the included studies (e.g., differing sub-dimensions and a predominance of self-reported over performance-based or observational measures of instructional quality). The pooled correlations should therefore be read as synthesizing a self-report-dominated evidence base rather than a fully construct-equivalent one. Fifth, because most primary studies reported only a subset of the three pairwise relationships, the Stage 2 correlation matrix was assembled from three independently pooled bivariate meta-analyses rather than a single joint multivariate synthesis. This simplification does not fully model the statistical dependence introduced when a single study contributes to more than one cluster. Sixth, given the small number of studies per cluster (k = 7–13), formal moderator or subgroup analyses were judged to be underpowered and were not conducted.

To address these limitations, future research should prioritize longitudinal and experimental designs; use objective measures of instructional quality (e.g., classroom observation, video-coded lesson analysis, or student outcomes) alongside self-report, where a larger and more contextually homogeneous set of primary studies becomes available, revisit the mediating role of Self-Efficacy with adequate statistical power to resolve the ambiguity reported here. In the present study, the indirect effect's confidence interval was obtained via the Wald/delta method. Genuine resampling-based bootstrap confidence intervals could not be obtained for a correlation-matrix-based structural model within the software environments available to us, and remain a worthwhile target for future replications with access to individual-participant primary data or specialized resampling tools for meta-analytic SEM.

Conflict of Interest

The author states that there is no conflict of interest.

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