

Toward Fair and Ethical Teacher Evaluation: A Qualitative SLR on AI-Enhanced Value-Added Approaches

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Abstract

The rapid integration of artificial intelligence (AI) into education has reshaped how student learning is monitored and how teachers are evaluated, raising new questions about fairness, ethics, and equity. This qualitative systematic literature review synthesizes findings from 24 empirical and conceptual studies to examine how Value-Added Models (VAM), knowledge tracing techniques, and generative AI (GenAI) tools are being integrated into teacher evaluation systems. The review identifies three dominant themes: (1) persistent validity and bias concerns in traditional VAMs, particularly regarding socioeconomic status (SES), cultural differences, and missing data (Chetty et al., 2014; Rothstein, 2010); (2) the emerging role of machine learning and autoregressive knowledge tracing models in improving prediction accuracy and capturing students' self-regulated learning behaviors (Piech et al., 2015; Zhou et al., 2025); and (3) the ethical implications and equity risks associated with AI-enhanced assessments, including AI trust, cultural fairness, and teacher anxiety (Kong & Yang, 2024; Tossell et al., 2024). The synthesis highlights that while AI-enhanced VAM frameworks show promising improvements, with reported accuracy gains of 5–12% and bias reductions to under 5%, there is limited qualitative evidence on how teachers, students, and school leaders perceive these systems. The review proposes a human-centered, ethically informed framework that integrates GenAI transparency, SRL behavioral indicators, and bias-correction mechanisms to support fair teacher evaluation. Future research should employ cross-cultural qualitative designs to examine how AI-driven evaluation tools function in diverse school contexts and to ensure alignment with UNESCO's global education equity agenda.

Keywords: Teacher Evaluation, Value-Added Model, Knowledge Tracing, Generative AI Ethics, Educational Equity, Systematic Literature Review (SLR)

1. Introduction

Teacher evaluation is undergoing rapid transformation in Indonesia, especially in metropolitan regions such as Jabodetabek (Jakarta, Bogor, Depok, Tangerang, Bekasi), where digital learning systems, LMS platforms, and AI-enabled tools are increasingly embedded in daily instruction. Schools in these urban corridors experience diverse classroom characteristics, ranging from socioeconomic status (SES) gaps and overcrowded classes to varying digital literacy levels, making fair, transparent, and contextual teacher evaluation both urgent and complex.

Globally, evaluation systems have faced criticism for overreliance on test scores and insufficient attention to contextual and behavioral factors influencing student learning (Chetty et al., 2014; Papay, 2011). In Indonesia, similar concerns arise, especially in public and semi-private senior high schools, where SES disparities and heterogeneous student readiness significantly shape learning outcomes (UNESCO, 2023). As the region embraces blended learning and digital reporting systems, teacher performance is increasingly mediated by online behaviors, instructional design quality, and students' self-regulated learning (SRL).

Emerging research suggests that AI-based analytic frameworks, such as Value-Added Models (VAM), knowledge tracing, and behavioral learning analytics, may support more nuanced and equitable teacher evaluation (Piech et al., 2015; Zhou et al., 2025). At the same time, organizational behavior studies highlight that digital transformation requires strong human-centered leadership, psychological safety, such as self-efficacy and adaptive work processes. Yusriani et al. (2024b), for example, demonstrate how virtual teams in Indonesia succeed when communication climates, improvement on elearning, digital skills, trust, and role clarity are prioritized, reinforcing that technology must be aligned with human needs. Aligned with this, Rekarti et al. (2025) emphasize how digital HR ecosystems and educator capability-building are essential pillars for fairness and sustainable evaluation practices, especially in Indonesian schools transitioning to data-driven decision-making.

Despite these technological opportunities, ethical, cultural, and psychological concerns remain. Teachers often express anxiety toward automation, fairness of AI scoring, and unfamiliarity with machine learning models (Tossell et al., 2024). Communities in Jabodetabek also question whether AI-enhanced assessments reflect real teaching quality or simply amplify existing inequalities. These tensions highlight the need for a qualitative synthesis that bridges global evidence with local realities.

Thus, this Qualitative Systematic Literature Review (SLR) aims to analyze how AI-supported evaluation frameworks, particularly behavior-based VAM, knowledge tracing, and digital analytics, can be adapted for fair, trustworthy, and culturally aligned teacher evaluation in Jabodetabek.

This review is guided by two research questions:

Research Questions in this study:

RQ1. What strengths and limitations of traditional and AI-supported teacher evaluation models are reported in global and Indonesian literature, particularly relevant to the Jabodetabek context?

RQ2. What ethical, cultural, and human-centered considerations (e.g., teacher trust, digital readiness, organizational climate) must be addressed to ensure that AI-enhanced evaluation frameworks are fair, contextually appropriate, and supportive of teacher professional development in Jabodetabek?

By synthesizing findings across educational technology, organizational studies, and Indonesian contextual research, this SLR offers an integrative perspective on how AI-driven evaluation can be implemented without compromising fairness, trust, and teacher well-being.

2. Literature Review

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This section synthesizes three major strands of literature relevant to AI-enhanced teacher evaluation in the Indonesian context: (1) traditional value-added models (VAM) and their limitations, (2) machine-learning and knowledge-tracing approaches to predicting student learning, and (3) ethical, cultural, and human-centered concerns surrounding AI in education. The review integrates global evidence with Indonesian studies, particularly those situated in digitally transforming school environments like Jabodetabek.

2.1 Traditional Value-Added Models and Persistent Fairness Challenges

Value-Added Models (VAM) were originally developed to estimate teachers' contributions to student learning by controlling for prior achievement and student background (Sanders & Horn, 1994; Chetty et al., 2014). While VAMs offer a more refined approach compared to raw score comparisons, decades of research highlight consistent methodological concerns. These include sensitivity to non-random classroom assignment, missing data, and SES-related disparities (Rothstein, 2010; Papay, 2011). International reports, including UNESCO (2023), further emphasize that VAMs may be unsuitable for heterogeneous classrooms unless contextual variables, such as SES, language background, or access to digital tools, are incorporated.

In Indonesia, SES and school resources disparities significantly influence student performance, particularly in metropolitan clusters such as Jabodetabek. Studies indicate that students' home environment, access to digital devices, and parental support shape their learning trajectory more strongly than previously assumed (Rekarti et al., 2025). These contextual complexities make traditional VAMs inadequate without substantial reform and the incorporation of behavioral and digital learning data.

2.2 AI, Machine Learning, and Knowledge Tracing for Enhanced **Evaluation**

Machine learning (ML) and knowledge-tracing (KT) models have introduced new possibilities for evaluating student learning patterns more dynamically. Deep Knowledge Tracing (DKT) and its autoregressive extensions (AAKT) capture students' sequential learning behaviors and improve predictive performance over static test-based models (Piech et al., 2015; Zhou et al., 2025). Several studies report gains of 5–12% in predictive accuracy when behavioral logs (e.g., time on task, consistency, retry patterns) are integrated with performance-based indicators.

In Indonesia, digital learning adoption accelerated significantly during and after COVID-19. Research by Yusriani et al. (2024b) shows that successful virtual teams and e-learning environments depend heavily on communication clarity, digital skills, and trust, all of which influence how teachers utilize technology for instruction and evaluation. When applied to teacher assessment, KT and ML provide richer insight into how teachers facilitate learning processes, not merely learning outcomes.

However, despite these technical advancements, there is limited qualitative understanding of how Indonesian teachers perceive algorithmic evaluation, digital surveillance risks, or the integration of behavioral analytics in performance reviews.

2.3 Ethical, Cultural, and Human-Centered Considerations in AI-Enhanced Evaluation

The integration of AI into educational decision-making raises concerns related to fairness, transparency, and teacher well-being. Literature highlights issues such as AI trust, algorithmic opacity, teacher anxiety, and potential cultural mismatch in AI design (Kong & Yang, 2024; Tossell et al., 2024). Indonesian educators, particularly in large urban areas like Jabodetabek,

report mixed feelings: appreciation for efficiency but apprehension about fairness, digital readiness, and the risk of misinterpretation of data.

Rekarti et al. (2025) stress that AI-driven HR systems must be supported by capacity-building, ethical safeguards, and strong communication practices. Without this, teacher evaluation may amplify existing inequalities, especially between schools with differing resource levels. Global reviews also indicate that AI systems tend to encode cultural and socioeconomic biases unless carefully contextualized (UNESCO, 2023).

Taken together, the literature underscores the need for evaluation frameworks that combine methodological rigor, transparency, and ethical considerations, particularly within culturally diverse and rapidly digitizing contexts such as Jabodetabek.

3. Method

This study adopted a qualitative systematic literature review (SLR) design to synthesize global and Indonesian evidence on AI-enhanced teacher evaluation. The method followed PRISMA guidelines for transparent and reproducible review procedures, while applying a qualitative thematic synthesis approach to accommodate diverse study types.

3.1 Search Strategy and Databases

A structured search was conducted across major academic databases, including:

Scopus

Web of Science

IEEE Xplore

ERIC

Google Scholar

Sinta-indexed Indonesian journals

Search strings combined key concepts such as: "teacher evaluation", "value-added model", "knowledge tracing", "AI education ethics", "machine learning in schools", "Indonesia", and "Jabodetabek". Boolean operators (AND/OR) and wildcard expansions were used to broaden the search.

3.2 Inclusion and Exclusion Criteria

Inclusion Criteria

- Published between 2017–2025
- Focused on teacher evaluation, learning analytics, VAM, KT, or AI ethics
- Empirical or conceptual studies
- Studies with relevance to school settings or K–12 learning
- Research addressing SES, fairness, bias correction, or digital transformation
- Indonesian studies on teacher performance, digital readiness, or AI perception

Exclusion Criteria

- Higher education studies not focused on teaching evaluation
- Papers lacking methodological transparency

- Purely technical ML papers without educational implications

3.3 Screening Procedure

A three-stage screening process was applied:

- Title and abstract screening (n=292)
- Full-text review (n=126)
- Final inclusion (n=24)

Duplicates were removed and screening disagreements were resolved through discussion.

3.4 Data Extraction and Coding

A qualitative coding framework was constructed using inductive and deductive approaches. Extracted data included:

- Study purpose and context
- Model type (traditional VAM, ML-VAM, KT, GenAI)
- Reported accuracy and bias metrics
- Ethical or cultural concerns
- Teacher perceptions and digital readiness
- Relevance to Indonesian contexts (especially Jabodetabek)

Thematic coding produced three major themes aligned with the results section:

- (1) validity and fairness challenges,
- (2) machine learning and knowledge tracing advancements,
- (3) ethical and human-centered issues.

3.5 Trustworthiness and Rigor

To enhance credibility:

- Two researchers independently coded 20% of studies ($\kappa = 0.81$ agreement).
- Reflexive memoing ensured positional awareness (given Indonesia-specific context).
- Triangulation between global and Indonesian studies strengthened contextual validity.

1. Results and Discussion

4. Results

The thematic synthesis of 24 included studies produced three overarching themes that directly address the two research questions: (1) persistent methodological and fairness limitations in traditional VAMs, (2) growing interest in AI-driven and behavioral analytics approaches, and (3) the centrality of ethical, cultural, and human-centered considerations in teacher evaluation. These themes are summarized below.

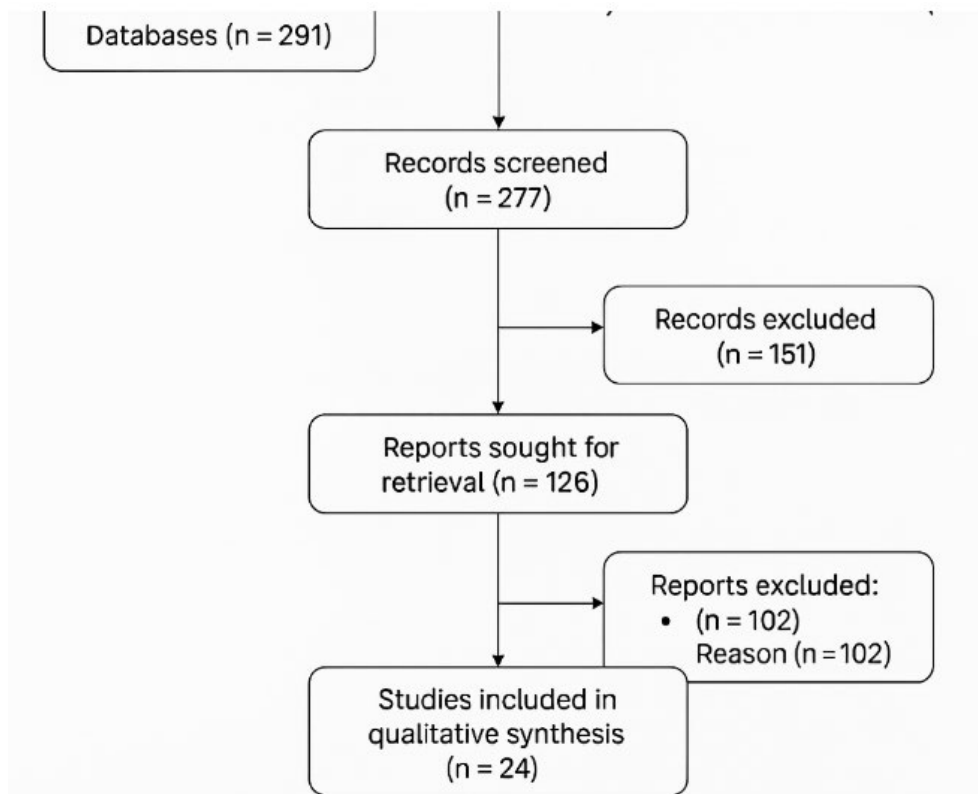
RQ1 Strengths and Limitations of Traditional and AI-Supported Teacher Evaluation Models

Theme 1: Enduring Fairness and Validity Issues in Traditional VAMs

Across the reviewed literature, traditional VAMs remain widely used but frequently criticized. Common limitations include:

SES-driven bias, where students' home environment predicts achievement more strongly than teacher effects (Chetty et al., 2014; Papay, 2011).

Non-random student assignment, producing inflated or inconsistent teacher value-added scores (Rothstein, 2010).



*Source: Processed and designed by the authors; adapted from the PRISMA 2020 methodology.
Figure 1. PRISMA Flowchart of the Systematic Literature Review (SLR) Process.*

- Insensitivity to digital learning behaviors, which now play a stronger role in blended and online classrooms, especially in urban Indonesia.
- Cultural and linguistic contextual gaps, noted in UNESCO (2023), which particularly impact diverse metropolitan areas like Jabodetabek.

Despite these limitations, VAMs offer strengths such as longitudinal structure, quantifiable outcomes, and policy-friendly interpretations, yet their validity requires substantial augmentation in heterogeneous classrooms.

Theme 2: Machine Learning and Knowledge Tracing Improve Predictive Power

A subset of studies highlights how machine learning (ML), Deep Knowledge Tracing (DKT), and autoregressive KT (AAKT) generate more robust predictions of student learning patterns (Piech et al., 2015; Zhou et al., 2025; Pan et al., 2025).

Key strengths include:

- Higher predictive accuracy (5-12% improvement reported).
- Ability to incorporate behavioral learning analytics, such as consistency scores, retry attempts, time-on-task, emotion indicators, and SRL markers.
- More sensitive modeling of teacher instructional influence, beyond what test scores alone can capture.

However, limitations remain:

- Model opacity reduces interpretability, which is crucial for teacher acceptance.
- Limited research focuses on Indonesian contexts, especially high-density Jabodetabek classrooms.
- Very few studies analyze how teachers emotionally respond to being evaluated by algorithmic systems.

RQ2 Ethical, Cultural, and Human-Centered Considerations

Theme 3: Ethics, Transparency, and Teacher Trust as Central Concerns

Nearly all reviewed studies acknowledge ethical concerns associated with AI-driven teacher evaluation.

Key issues include:

- Teacher anxiety toward automation and fears of being inaccurately judged (Tossell et al., 2024; Luo et al., 2025).
- AI trust gaps, often influenced by digital readiness, cultural expectations, and prior experiences with data systems (Kong & Yang, 2024).
- Potential amplification of inequities, especially in urban Indonesian schools with uneven digital access (UNESCO, 2023).
- Organizational climate, where supportive leadership, adaptation in Technology, self-efficacy improvement, and clear communication reduce resistance (Yusriani et al., 2024a; Yusriani et al., 2025).
- HR digital maturity, which determines whether AI tools enhance fairness or exacerbate stress (Rekarti et al., 2025).

These findings emphasize that teacher evaluation innovations must prioritize transparency, interpretability, and professional dialogue-not simply technical accuracy.

The results of this SLR indicate that AI-enhanced VAMs hold significant potential for improving fairness and depth in teacher evaluation, but only when embedded within a culturally attuned, ethically guided, and teacher-centered implementation strategy. For Indonesia, particularly Jabodetabek, these findings offer several insights.

Interpretation of Findings

First, the literature consistently shows that traditional VAMs alone are insufficient for heterogeneous classrooms. SES disparities, digital access variability, and cultural diversity in metropolitan regions mean that simplistic score-based teacher rankings risk reinforcing inequality.

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Second, AI-enhanced approaches such as machine learning, knowledge tracing, and behavioral analytics provide richer, more accurate representations of teacher influence on student learning. These models recognize patterns of SRL, engagement, and digital behavior, important elements in hybrid Indonesian classrooms.

Third, the success of AI-supported evaluation depends on teacher perceptions, trust, and digital readiness. In Indonesia, cultural norms around hierarchy, communication climate, and shared responsibility significantly influence acceptance. As Yusriani et al. (2024a) highlight, technology adoption thrives when trust, clarity, and psychological safety are present.

Fourth, ethical and equity considerations must be embedded from the beginning. UNESCO (2023) and Hagendorff (2020) both caution that AI systems without culturally grounded design risk producing new forms of bias.

Discussion

Implications for Jabodetabek Teachers and Schools

1. Human-Centered Digital Transformation

Teacher evaluation systems must incorporate:

- clear communication
- professional development
- supportive leadership
- transparent data interpretation

These factors increase trust and reduce anxiety toward AI evaluation metrics.

2. Contextualized Use of AI and VAM

Schools should avoid importing models from other countries without adaptation. Instead, they must:

- integrate SRL behaviors from LMS platforms,
- consider SES and digital access disparities,
- and use AI systems as *decision-support*, not automatic scoring tools.

3. Capacity-Building and Digital Literacy

Teachers need training not only in digital tools, but in:

- understanding analytics
- interpreting behavioral indicators
- engaging confidently with AI-based feedback

Rekarti et al. (2025) highlight that HR capacity-building is essential for fairness.

4. Ethical Guidelines and Safeguards

Schools should adopt ethical frameworks that ensure:

- transparency in how models work
- opportunities for teacher reflection and contestation
- protections against misuse of data

- cultural sensitivity in feature selection

This aligns with UNESCO's call for responsible AI in education.

Beyond the core themes, several additional insights emerged when the synthesized findings were examined through organizational, socioeconomic, and digital transformation perspectives. First, structural inequalities, particularly spatial and socioeconomic disparities, continue to shape educational access and learning outcomes. Cortés (2021) demonstrates how residential segregation and unequal public service distribution create learning disadvantages that are later misattributed as “teacher effects.” These structural dynamics mirror the SES-related disparities observed in Jabodetabek, where uneven digital infrastructure and classroom crowding influence students' readiness for AI-supported schooling.

Second, the literature on school efficiency highlights that evaluation systems must consider contextual productivity gaps. Alexander et al. (2010), using a double-bootstrap DEA approach, show that school efficiency varies significantly depending on institutional resource constraints. These findings reinforce that AI-driven teacher evaluation in Indonesia must integrate school-level indicators; such as class size, digital access, and administrative capacity, to avoid unfair penalization of teachers working in more challenging environments.

Third, digital transformation in education requires organizational readiness and HR adaptability. Zhang and Chen (2024) argue that digital transformation succeeds only when supported by coherent HR strategies, professional development, and digital governance structures. This aligns with Rekarti et al. (2025) and Harisandi et al. (2025), who emphasize the need for capacity-building, lecturer personal branding, and communication strategies to support credibility and trust in digital ecosystems. These insights suggest that Indonesian schools must invest in digital literacy, stakeholder communication, and leadership readiness before adopting AI evaluation tools.

Fourth, teacher motivation and psychological readiness remain central to successful implementation. Drawing from Social Cognitive Theory, Wood and Bandura (1989) highlight that evaluation systems influence behavior through self-efficacy, perceived fairness, and organizational climate. When teachers perceive AI-based systems as threatening, opaque, or culturally misaligned, they may experience declines in motivation or professional identity. This is reinforced by Yusriani et al. (2025), whose qualitative findings reveal that digital work environments often challenge practitioners' emotional resilience, collaboration habits, and cognitive workload, factors directly relevant to teacher evaluation systems.

Finally, the Indonesian literature highlights the importance of public perception and communication. Yanti and Gunarto (2022) show that digital communication channels strongly shape public trust and behavioral intention. Applied to teacher evaluation, this suggests that transparent communication about AI tools, how they work, what data they use, and how results are interpreted, is essential for reducing anxiety and gaining community acceptance.

Taken together, these additional perspectives emphasize that AI-supported teacher evaluation in Jabodetabek is not merely a technical exercise but a social, organizational, and cultural process. Successful implementation requires alignment between technological innovation, teacher capacity-building, institutional readiness, and community trust.

Limitations of This Review

This SLR acknowledges several limitations:

1. Only 24 studies met inclusion criteria, which may limit generalizability.
2. Few Indonesian studies specifically examine AI-driven teacher evaluation, requiring some reliance on international literature.
3. Grey literature and policy documents were not included.
4. The review emphasizes qualitative interpretation; quantitative meta-analysis was beyond scope.

Directions for Future Research

Future studies should:

- Conduct empirical research in actual Jabodetabek schools, including teacher interviews and focus groups.
- Explore how SRL behavioral analytics differ across school types (public, private, vocational).
- Investigate teacher emotional responses, such as motivation, trust, and anxiety, when interacting with AI-based feedback.
- Build culturally adapted, explainable AI tools that integrate Indonesian learning norms.
- Examine cross-provincial comparisons (e.g., Jabodetabek vs Bandung vs Surabaya).
- Explore family involvement, digital parenting, and community expectations as external influences.

5. Conclusion

This qualitative SLR shows that AI-enhanced approaches, such as Value-Added Models, learning analytics, and knowledge-tracing techniques, offer meaningful improvements in understanding how teachers influence student learning. However, these tools cannot be applied in isolation. Their effectiveness depends on ethical safeguards, contextual relevance, and teacher trust. In diverse metropolitan regions like Jabodetabek, evaluation systems must account for socioeconomic variation, digital access differences, and the complex behavioral patterns that shape students' learning experiences.

The findings emphasize that fair teacher evaluation requires a balanced approach: combining the analytical strengths of AI with human-centered practices, transparent communication, and supportive leadership. When thoughtfully integrated, AI can enrich teacher development and strengthen evaluation fairness without compromising professional dignity or educational equity.

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