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The Relationship Between Teachers' Machine Learning Competence and Improvements in Islamic Education Achievement Among Students at Al Uswah Islamic Junior High School

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A B S T R A C T

Digital transformation encourages the integration of machine learning (ML) as a strategic instrument for improving Islamic Religious Education (PAI) learning quality. This study aims to analyze the relationship between teachers' ML competence and PAI learning achievement of students at SMP IT Al Uswah. A mixed methods approach with sequential explanatory design was employed. Respondents consisted of 8 PAI teachers and 124 students from grades VII–IX. Quantitative data were collected through a 40-item Likert scale questionnaire, report card grades, and digital formative assessment scores; analyzed using SEM-PLS (SmartPLS 4.0). Qualitative data were obtained through in-depth interviews with 6 informants, classroom observation over 12 sessions, and documentation study. Results indicate that teachers' ML competence is at a moderate level (mean = 3.41; SD = 0.54). The data literacy dimension obtained the highest score (mean = 3.78), while predictive pedagogical intervention was the lowest (mean = 3.02). Students' average PAI learning achievement was 81.6 (SD = 6.4). SEM-PLS analysis shows a positive and significant relationship between teachers' ML competence and PAI learning achievement (β = 0.612; t = 7.84; $p < 0.001$; $R^2 = 0.462$). AI-based pedagogical mechanisms identified include the use of Quizizz Analytics, Google Classroom insights, and the Edmodo platform. These findings confirm the need for structured ML training programs for PAI teachers in integrated Islamic schools

INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) has shifted the global educational paradigm toward adaptive, personalized, and predictive data-driven learning. As a major branch of AI, machine learning (ML) enables educational systems to analyze student learning patterns, recommend materials tailored to individual needs, and predict potential academic failure at an early stage. This technological transformation demands a paradigm shift in the teacher's role from a mere content deliverer to a designer of data-driven, intelligent learning experiences.

The efficacy of incorporating machine learning in education is heavily determined by teachers' proficiency in mastering this technology. This includes data literacy, the deployment of learning analytics, the capacity to personalize instructional materials, and the skill to execute pedagogical interventions based on predictive systems. Conversely, empirical evidence indicates that low digital competence among educators serves as a primary barrier to successful AI implementation in schools (Alam et al., 2024; Susilowati et al., 2025).

In the context of Islamic Religious Education (IRE), the integration of machine learning holds strategic potential to enhance student learning outcomes through adaptive learning environments, automated feedback mechanisms, and differentiated instruction tailored to students' unique religious and cognitive characteristics. Nevertheless, most integrated Islamic schools in Indonesia predominantly utilize digital technology for administrative workflows rather than adopting it as an AI-driven pedagogical tool (Murniyetti et al., 2023; Rahayuningsih & Muhtar, 2022; Mishra & Koehler, 2006).

SMP IT Al Uswah, an integrated Islamic junior high school, has implemented a digital learning ecosystem since 2022 leveraging the Google Classroom and Edmodo platforms. However, a preliminary assessment revealed that the utilization of learning analytics and ML features on these platforms remains highly constrained. Teachers generally confine their use to assignment distribution and digital attendance tracking, leaving the platform's advanced analytical capabilities largely untapped. This gap between technological potential and actual pedagogical practices correlates with fluctuations in students' academic performance in IRE.

LITERATURE RIVIEW

While previous scholarship has extensively examined the broader application of AI in education (Holmes et al., 2023; Luckin et al., 2016; Miao et al., 2021) , empirical studies specifically analyzing the relationship between teachers' machine learning proficiency and students' IRE learning achievements in integrated Islamic schools remain scarce. To address this literature gap, the present study aims to: Analyze the level of ML competency among IRE teachers at SMP IT Al Uswah; Analyze the level of ML competency among IRE teachers at SMP IT Al Uswah; Test the significance of the relationship between these two variables; Identify the resulting AI-based pedagogical mechanisms within the school.

METHODOLOGY

Sequential Explanatory Design

This study employed a mixed-methods approach utilizing a sequential explanatory design (Braun & Clarke, 2006). The initial phase involved collecting and analyzing quantitative data to test hypothesized causal relationships among variables through survey instruments and SEM-PLS. The subsequent phase involved gathering qualitative data through in-depth interviews, classroom observations, and document analysis to further interpret, contextualize, and elaborate upon the quantitative insights. The investigation was conducted at SMP IT Al Uswah Tuban, East Java, from February to June 2026.

The research population comprised all active IRE teachers (N = 8) and students in grades VII–IX (N = 124) at SMP IT Al Uswah. The student cohort was distributed as follows: 42 seventh-grade students, 41 eighth-grade students, and 41 ninth-grade students. Given the manageable size of the population, total sampling was adopted, meaning the entire population served as respondents. For the qualitative phase, six informants were selected via purposive sampling: the school principal, three IRE teachers (representing the highest, median, and lowest questionnaire scores), and two students (one high-achieving and one average-achieving student).

The data collection instruments consisted of:

1. Teacher ML Competency Questionnaire: A 40-item instrument utilizing a 1–5 Likert scale, developed based on the DigCompEdu framework (Redecker & Punie, 2017) and AI Literacy guidelines (Ng et al., 2021). It encompasses four core dimensions: data literacy (10 items), learning analytics (10 items), adaptive content personalization (10 items), and predictive pedagogical interventions (10 items). Content validity evaluated by two experts yielded a Content Validity Ratio (CVR) of 0.87 (highly valid) , while internal consistency reliability was confirmed via Cronbach's Alpha ($\alpha = 0.891$; highly reliable).
2. Academic Documentation: Official academic report card grades for the second semester of the 2025/2026 academic year alongside digital formative assessment scores retrieved from Quizizz.
3. Qualitative Tools: Semi-structured interview protocols and a structured classroom observation sheet consisting of 12 distinct indicators.

Quantitative data were processed via SEM-PLS using SmartPLS 4.0 through a two-stage evaluation:

- Measurement Model (Outer Model): Validated using Convergent Validity (AVE > 0.5), Discriminant Validity (HTMT < 0.85), and Composite Reliability (CR> 0.7).
- Structural Model (Inner Model): Assessed through path coefficients (β), t-statistic values (> 1.96), and the coefficient of determination (R2)

Qualitative data were subjected to thematic analysis employing open, axial, and selective coding strategies (Braun & Clarke, 2006). Source and method triangulation were strictly applied to ensure data credibility and trustworthiness.

RESULT

The study was carried out at SMP IT Al Uswah, situated in Sugiharjo Village, Tuban. Established in 2015 under the Al Uswah Foundation, the institution currently manages 12 classrooms with an aggregate enrollment of 378 students. The school integrated a digital learning system powered by Google Workspace for Education and Edmodo starting in the 2022/2023 academic year. The 8 participating IRE teachers exhibited the following demographic profiles: 5 females and 3 males; an age range of 26–44 years (mean= 33.6 years); years of service ranging from 2–16 years (mean= 7.8 years); and educational backgrounds consisting of bachelor's degrees (5 individuals) and master's degrees (3 individuals). The distribution of the 124 student respondents across different grade levels is presented in Table 1

Table 1. Distribution of Student Respondents at SMP IT Al Uswah

Grade	Male	Female	Total	Average IRE Score
Grade	Male	Female	Total	Average IRE Score
VII	22	20	42	82.4
VIII	21	20	41	81.3
IX	20	21	41	81.2
Total	63	61		

Field documentation gathered under the explicit authorization of the school principal (dated Maret 10, 2026) included classroom observation photographs, user interface screenshots of Quizizz Analytics and Google Classroom dashboards, and digital grade records.

Results of Instrument Validity and Reliability Testing

Prior to field deployment, a pilot test of the instrument was conducted with 30 IRE teachers outside the primary research sample who possessed equivalent characteristics. The measurement model evaluation results are detailed in Table 2.

Table 2. Validity and Reliability Assessment of the Teacher ML Competence Instrument

Dimension	AVE	CR	Cronbach's Alpha	Description
Data Literacy (DL)	0.623	0.901	0.876	Valid & Reliable
Learning Analytics (LA)	0.587	0.887	0.851	Valid & Reliable
Personalized Content (PC)	0.601	0.894	0.863	Valid & Reliable
Predictive Intervention (PI)	0.578	0.882	0.847	Valid & Reliable
ML Competence (Overall)	0.597	0.891	0.891	Valid & Reliable

(Source: SmartPLS 4.0 Output, 2026)

All latent constructs successfully satisfied the threshold requirements of AVE > 0.5 and CR> 0.7 (Hair et al., 2017), substantiating rigorous convergent validity and composite reliability. Furthermore, discriminant validity evaluated via the Heterotrait-Monotrait Ratio (HTMT) criterion demonstrated that all values fell below 0.85, confirming the absence of multicollinearity issues among the underlying constructs (Murniyetti et al., 2023; Kumar & Parveen, 2022; Juliyanti & Angraini, 2026).

Level of Machine Learning Competence Among IRE Teachers

Descriptive statistics mapping the ML competence levels among the eight IRE educators are summarized in Table 3. Score evaluation thresholds were categorized as: very low (1.00–1.80), low (1.81–2.60), moderate (2.61–3.40), high (3.41–4.20), and very high (4.21–5.00).

Table 3. Descriptive Breakdown of Teachers' Machine Learning Competencies

Dimension	Mean	SD	Min	Max	Category
Data Literacy (DL)	3.78	0.42	3.10	4.50	High
Learning Analytics (LA)	3.45	0.51	2.80	4.20	High
Personalized Materials (PM)	3.38	0.58	2.60	4.10	Moderate
Predictive Intervention (PI)	3.02	0.63	2.20	3.80	Moderate
ML Competency (Overall)	3.41	0.54	2.68	4.15	High

(Source: Descriptives Output, 2026)

As shown in Table 3, teachers' cumulative ML competence scored in the high band (mean= 3.41). The data literacy dimension yielded the highest score (mean = 3.78; High), highlighting that educators are capable of interpreting foundational learning metrics—including daily quiz summary metrics and progression charts integrated into Google Classroom. While the learning analytics dimension scored high (mean = 3.45), it displayed a broader variance (SD= 0.51), reflecting diverse skill distributions across individuals.

In contrast, predictive pedagogical intervention registered the lowest score (mean= 3.02; Moderate). This points to a deficit in using predictive platform algorithms to craft proactive, pre-emptive interventions before students struggle academically. This finding aligns with Juliyanti and Angraini (2026), who noted that Indonesian educators' technological proficiency commonly peaks at moderate levels, particularly concerning advanced AI capabilities.

Distinct individual disparities were apparent: teacher G-03 (28 years old, 3 years of service, Master's in Learning Technology) attained the peak score (mean = 4.15), whereas teacher G-07 (44 years old, 16 years of service, Bachelor's in Islamic Education) scored the lowest (mean= 2.68). This pattern hints that age, experience, and educational background may impact competency levels, though small sample constraints ($n = 8$) preclude definitive statistical generalizations.

Students' IRE Learning Achievement

Student learning data were derived from semester-end report card grades and individual digital formative check-ins executed through Quizizz (requiring a minimum of 8 quizzes per student over the semester).

Table 4. Profile of Student IRE Academic Performance (N = 124)

Component	Mean	SD	Min	Max	Passing Score	% ≥ Passing Score
IRE Report Card Score	81.6	6.4	67	97	75	91.1%
Quizizz Score (Formative)	78.3	8.7	55	98	70	85.5%
Cognitive Domain	82.1	7.2	65	98	75	92.7%
Affective Domain	83.4	5.8	70	97	75	95.2%
Psychomotor Domain	79.4	6.9				

(Source: Documentation Analysis, 2026)

The average report card mark stood at 81.6 (SD = 6.4), with 91.1% of the student body surpassing the minimum passing benchmark of 75. Across core instructional domains, the affective domain scored highest (mean = 83.4), while the psychomotor domain lagged (mean= 79.4). This disparity is understandable given that integrated Islamic schools emphasize immersive religious character models, driving higher affective marks, while formal physical practice parameters require ongoing refinement. A total of 11 students (8.9%) failed to meet passing standards, distributed across grade VII (6 students), grade VIII (3 students), and grade IX (2 students). This aligns with field observations indicating that grade VII classrooms guided by instructors with lower ML competencies showed a higher density of underachieving students.

SEM-PLS Test Results: The Relationship Between ML Competence and IRE Academic Achievement

Hypothesis testing was executed using SmartPLS 4.0 via bootstrapping with 5,000 subsamples. The structural framework treated teachers' ML competence (X) as an exogenous variable (with four dimensions acting as reflective indicators) and student IRE academic outcomes (Y) as the endogenous variable.

Table 5. SEM-PLS Structural Model Outputs

Relationship Paths	β (Path Coeff.)	T-Statistic	P-Value	Description
ML Competence →IRE Achievement	0.612	7.84	< 0.001	Significant (H1 Accepted)
Data Literacy →IRE Achievement	0.487	5.23	< 0.001	Significant
Learning Analytics → IRE Achievement	0.534	6.11	< 0.001	Significant

Personalization of Materials →IRE Achievement	0.501	5.67	< 0.001	Significant
Predictive Intervention →IRE Achievement	0.443	4.89		

(Source: SmartPLS 4.0 Processing, 2026. Note: T-statistic >1.96 indicates significance at α = 0.05; R2 = 0.462; Predictive Relevance Q2 = 0.381)

The modeling results revealed a path coefficient (β) of 0.612, a t-statistic of 7.84, and P < 0.001, strongly validating a positive and significant relationship between teachers' ML competencies and student outcomes (accepting H1). The R2 value of 0.462 establishes that 46.2% of the variance in student IRE outcomes is directly explained by teacher ML competence, a moderate-to-large effect size in behavioral and social research (Hair et al., 2017).

Among the distinct competency branches, learning analytics exerted the strongest influence (β = 0.534), followed by material personalization (β = 0.501), data literacy (β = 0.487), and predictive interventions (β = 0.443). This demonstrates that an educator's agility in reviewing and acting upon learning data in real-time serves as a vital component for driving student academic success. This pattern aligns with Siemens (2013), who posited learning analytics as an essential mechanism for data-driven educational optimization. In practice, real-time analytics from Quizizz and Google Classroom allow teachers to isolate challenging topics—such as the rules of tajwid (nun sakinah and tanwin) or muamalah concepts in fiqh—and deploy targeted remedies.

DISCUSSION

Qualitative Findings: AI-Based Pedagogical Mechanisms

Thematic analysis of the qualitative data mapped three main themes: (a) teacher habits regarding analytics platform use, (b) student adaptation patterns, and (c) systemic hurdles within an integrated Islamic school environment.

Practices in the Use of Analytics Platforms by IRE Teachers

Classroom observations across 12 sessions established that teachers regularly engaged with three primary tools: Google Classroom, Quizizz, and Edmodo. However, the level of feature usage varied widely. Teachers demonstrating high ML competence (G-03 and G-05) consistently evaluated the "Class Summary" logs on Quizizz to observe item-by-item student error rates. This allowed them to restructure remedial strategies for subsequent sessions. In class VIII-A managed by G-03, 87% of quiz items were analyzed differentially: questions with error rates exceeding 40% were re-taught to the entire class, while items falling in the 20–40% error zone were handled via individual enrichment assignments. During an interview, G-03 detailed this workflow:

"After every quiz, I first open the Class Summary on Quizizz. I look at which questions students got the most wrong. For example, if the question on tajwid idgham bighunnah was answered incorrectly by everyone, that means I need to change how I explain it. From there, I create a short video using CapCut

and upload it to Google Classroom. So the remediation isn't starting from scratch, but is targeted." (G-03, Interview, March 15, 2026).

Conversely, an instructor showing moderate competence (G-06) acknowledged reviewing only cumulative final grades without drilling down into deeper analytical markers:

"I use Quizizz for daily quizzes; the scores come out immediately. But to review which specific questions were missed, I rarely have the time. I'm short on time because I have to teach four classes in a single day." (G-06, Interview, March 18, 2026)

G-06's reflection highlights a major practical constraint: heavy teaching workloads present structural barriers to learning analytics optimization. The school principal confirmed this operational reality:

"We've subscribed to Google Workspace for Education Plus and Edmodo Premium. The features are comprehensive, and they include AI. But honestly, many teachers still don't know how to interpret the data there. We've scheduled training, but it's constrained by time because teachers also have other school activities." (Principal, Interview, March 20, 2026)

Figure 1. Interview Photo

Student Responses and Adaptation to AI-Based Learning

Students demonstrated high enthusiasm for digital learning environments, particularly when gamified features (points, live leaderboards, audio cues) were utilized. The average digital quiz participation rate hit 96.8%, notably higher than traditional paper-based exams (91.3%). A high-achieving student (S-14, IRE grade: 94) shared:

"Quizizz is great because you know right away where you went wrong. With regular exams, we only find out after the teacher has graded them—sometimes a week later. With Quizizz, you know immediately and can start studying again right away." (S-14, Interview, March 22, 2026)

An average-performing student (S-47, IRE grade: 78) added an alternative perspective:

"I like the quizzes, but sometimes I get a bit confused when the teacher explains using those data points. Like the graphs. But when the teacher says, 'Okay, this is a question many got wrong; let's go over it again,' then I understand and it helps." (S-47, Interview, March 22, 2026)

Classrooms led by high-ML-competent instructors demonstrated more dynamic discourse patterns, systematic wait times, and higher student query frequencies. Class VIII-A (G-03) averaged 14.3 questions per session, whereas Class VIII-B (G-06) averaged 8.7 questions.

Challenges of the Digital Ecosystem in Integrated Islamic School Environments

Three critical barriers were identified. First, a profound individual skill divide exists, with the score gap between the highest and lowest-performing teachers spanning 1.47 points on a 5-point scale. Second, infrastructure constraints persist; despite a 30-PC computer laboratory, network connectivity fluctuates, shifting from an average of 8.4 Mbps in morning sessions down to 3.2 Mbps in peak afternoon hours. Third, some educators show philosophical resistance, viewing algorithmic intervention as antithetical to spiritual and character-centric education. Teacher G-07 highlighted this perspective:

"I'm a bit concerned. If everyone uses AI, the children might become too dependent on technology. Religious education is fundamentally about heart-to-heart connection, not heart-to-machine. I still believe the best teacher is one who is present in a human way before their students." (G-07, Interview, March 25, 2026)

This philosophical concern aligns with the ethical educational AI questions outlined by Holmes et al. (2022) . The Ministry of Education and Culture's Directorate General of Curriculum and Instruction (2026) has emphasized that AI must function strictly as an instructional tool rather than an substitute for human mentorship. In religious instruction, this remains vital since spiritual growth cannot be automated through algorithms (Kim & Reeves, 2023; Long & Magerko, 2020). Stakeholders must demonstrate that ML integration handles tedious administrative tasks, allowing educators more time for meaningful human interaction with their students.

Integrative Discussion: Quantitative and Qualitative Synthesis

Blending quantitative modeling with qualitative observations provides a comprehensive overview of how teacher ML skills support student success. The positive structural path ($\beta = 0.612$, $R2 = 0.462$) operates via three pedagogical pathways:

1. Data-Driven Feedback Loops: Teachers evaluate performance metrics to formulate responsive remedial instructional designs.
2. Content Personalization: Teachers modify material formats based on student difficulty patterns identified by the platforms.
3. Motivation Enhancement: Gamified digital testing options stimulate engagement, improving learning quality.

These dynamics support the TPACK framework (Mishra & Koehler, 2006), which requires synergy across technological, pedagogical, and content knowledge. Teacher G-03, who demonstrated high TPACK skills by combining Quizizz Analytics (TK) with targeted remedial strategies (PK) for tajwid instruction (CK), achieved the highest average class marks (mean = 84.7). The prominent role of learning analytics ($\beta= 0.534$) confirms that real-time data literacy is a critical core competency in the modern AI educational era,

supporting the assertions of Siemens (2013) and Miao et al. (2021) . This study also expands upon Alam et al. (2024) by demonstrating these dynamics within the unique context of integrated Islamic schools and the multidimensional nature of the IRE curriculum.

Conversely, predictive pedagogical intervention showed the weakest influence (β= 0.443), reflecting low competency scores in this area (mean = 3.02). Teachers have not yet fully utilized predictive indicators—such as "At-Risk Student" logs on Google Classroom or "Student Progress Reports" on Edmodo—to implement proactive interventions. Consequently, targeted professional development programs focused on interpreting predictive data trends are highly recommended.

CONCLUSIONS AND RECOMMENDATIONS

This study empirically demonstrates a positive and significant relationship between teachers' competence in machine learning mastery and the IRE learning achievements of students at SMP IT Al Uswah (β= 0.612; t = 7.84; p < 0.001; R2 = 0.462). Among the four dimensions evaluated, learning analytics exerted the strongest influence on academic achievement (β= 0.534), followed by adaptive content personalization (β = 0.501), data literacy (β = 0.487), and predictive pedagogical interventions (β = 0.443). While teachers' overall ML competencies fall into the high category (mean = 3.41), a substantial individual skill gap remains (2.68 to 4.15) that requires systematic institutional attention.

Qualitatively, the AI-driven pedagogical mechanisms operate through data-analytic feedback loops, personalized remedial content planning, and gamified engagement strategies. Key challenges include individual competence divides, unstable network infrastructure, and philosophical resistance regarding AI use in character-focused religious education. Based on these findings, we recommend:

1. Designing structured ML training programs for IRE teachers, specifically focusing on learning analytics and predictive interventions.
2. Formulating professional development curricula that integrate Islamic ethical perspectives with modern AI applications.
3. Enhancing school internet infrastructure and bandwidth capacity.
4. Establishing AI-oriented regional IRE teacher communities of practice.
1. Future research should look to leverage broader sample sizes and experimental designs to establish stronger causal conclusions.

FURTHER STUDY

This research still has limitations, so further studies on the topic 'The Relationship Between Teachers' Machine Learning Competence and Improvements in Islamic Education Achievement Among Students' are needed to refine this research and provide more insights for the writer and readers.

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