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The Effect of Pedagogical Deep Learning on Mathematical Literacy: Moderating Role of Students' Digital Literacy

[1]*Muhammad Abdul Rohman, [2]Mohammad Syaifuddin, [3]Reni Dwi Susanti

Directorate of Postgraduate Program, Universitas Muhammadiyah Malang, Indonesia.

*Corresponding author e-mail: abdulrohman@webmail.umm.ac.id

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Abstract

Mathematical literacy remains a challenge in Indonesian education. Although digital technology is increasingly integrated, a theoretical gap remains regarding whether students' digital literacy merely correlates with outcomes or actively moderates pedagogical interventions. This study analyzed the effect of a pedagogical deep learning approach on students' mathematical literacy and investigated the continuous moderating role of digital literacy. The investigation utilized a quasi-experimental framework with non-equivalent control groups, implemented over six instructional sessions. The participant pool comprised 62 eleventh-grade learners from an Islamic educational institution, divided into a treatment cohort of 32 and a conventional group of 30. Empirical data were acquired through standardized PISA-aligned assessments alongside digital competency surveys, followed by evaluation utilizing an Analysis of Covariance. The findings demonstrated that the pedagogical deep learning approach yielded significantly higher mathematical literacy gains (mean N-Gain = 0.60) compared to conventional instruction (mean N-Gain = 0.27). However, the interaction between the instructional approach and continuous digital literacy was not statistically significant, indicating no statistically detectable moderation in this sample. The pedagogical quality of the deep learning intervention remained robust across varying student technological readiness levels. The study concludes that structured pedagogical design, rather than mere digital proficiency, primarily drives mathematical literacy development.

Keywords: Digital literacy; Mathematical literacy; Moderation analysis; Pedagogical deep learning.

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INTRODUCTION

The rapid development of digital technology has transformed educational practices and increased the demand for twenty-first-century competencies, including critical thinking, creativity, collaboration, communication, and digital literacy (Chiu, 2024; Tejedor et al., 2020). In mathematics education, digital technologies provide students with broader access to learning resources, support the visualization of abstract concepts, and facilitate engagement with authentic mathematical problems (Buentello-Montoya et al., 2021; Çakıroğlu et al., 2024; Yeung & Ng, 2023). However, the integration of technology alone does not necessarily lead to improved learning outcomes. Its educational effectiveness depends on how technology is pedagogically integrated and on the digital competencies of both students and teachers (Audrin & Audrin, 2022; Bond et al., 2020; Howard et al., 2021; Hung et al., 2025; Nguyen & Habók, 2024). Recent research also indicates that mathematics achievement is influenced by multiple individual, instructional, and contextual factors, highlighting the importance of shifting mathematics instruction from procedural learning toward deeper conceptual understanding (Ahmad et al., 2026; Muhaimin et al., 2024; Wang et al., 2023). The conceptual framework of mathematical literacy entails the cognitive aptitude to structure, apply, and evaluate

mathematical principles within practical scenarios to facilitate logical decision-making. This competency requires students to transition beyond basic arithmetic procedures to utilize analytical reasoning in solving everyday problems (Almarashdi & Jarrah, 2022; Bolstad, 2023; Mufidah et al., 2025; Situmeang et al., 2026). Despite its critical importance, Indonesian students continue to demonstrate low mathematical literacy performance. Recent global assessments from the 2022 Programme for International Student Assessment highlight a structural deficiency in this domain among Indonesian learners. The nation recorded a mean score of 366, positioning it 69th among 81 participating regions and trailing considerably behind the established OECD standard of 472 (Muhaimin et al., 2024; OECD, 2023). This disparity indicates persistent challenges in developing higher-order mathematical thinking skills and emphasizes the need for specialized instructional frameworks designed to maximize students' technological readiness and align with international assessment standards (Komarudin et al., 2024). The PISA framework specifically evaluates mathematical reasoning through tasks that demand critical, divergent, and convergent thinking, illustrating how students conceptualize meaning and subjectivity within mathematical instruction (Beccuti, 2024; Nurgabyl et al., 2023).

To address these persistent educational challenges, instructional approaches must be reoriented toward robust pedagogical frameworks. In the present study, deep learning is strictly defined as an instructional paradigm distinct from artificial intelligence algorithms. This pedagogical approach emphasizes deep conceptual understanding, knowledge integration, and the authentic application of information (Fullan & Langworthy, 2014; Talib et al., 2026; Yani T et al., 2026). Within the context of the Indonesian national education curriculum, this foundational deep learning theory is officially operationalized through a specific pedagogical framework consisting of three interconnected components: meaningful learning, mindful learning, and joyful learning (Siregar et al., 2025). These components directly support the fundamental cognitive processes required by the PISA mathematical literacy assessment (Maharini et al., 2026; Yenmez & Gökçe, 2023). Meaningful learning anchors abstract mathematical concepts into recognizable real-world contexts to facilitate problem formulation. Furthermore, mindful learning requires continuous metacognitive reflection to drive the interpreting phases, while joyful learning establishes an interactive collaborative environment that sustains the cognitive endurance necessary to execute complex procedures efficiently. Together, these interconnected principles effectively shift mathematics instruction from rote memorization toward active and reflective cognitive engagement (Ahmad et al., 2026; Situmeang et al., 2026). Such a structural transition is fundamentally required to equip learners with the analytical agility needed to deconstruct non-routine numerical problems. Consequently, mathematical knowledge is internalized as a functional mechanism for logical reasoning rather than remaining a static collection of isolated facts.

While pedagogical deep learning provides the primary instructional structure, digital literacy functions as a crucial operational factor in modern learning environments. To ensure exact alignment between theoretical definitions and measurement instruments, digital literacy in this study is operationalized specifically through four dimensions including communication, content creation, content utilization, and digital security (Falloon, 2020; Ilomäki et al., 2023; Talib et al., 2026; Zhao et al., 2021). Previous studies have established that digital literacy positively influences mathematical problem solving and academic achievement. However, there is a distinct theoretical gap regarding whether digital literacy merely correlates with learning outcomes or actively moderates the relationship between deep learning pedagogy and mathematical literacy (Wang et al., 2023; Yenmez & Gökçe, 2023). Digital literacy is expected to serve as a moderating variable because students with higher digital competencies may more effectively navigate content utilization and collaborative communication during meaningful learning activities, thereby amplifying the instructional benefits of the deep learning approach. Conversely, it is vital to determine whether high pedagogical quality alone can mitigate deficits

in students digital skills (Ahmad et al., 2026; Talib et al., 2026). Clarifying this exact interaction mechanism yields essential empirical evidence for educational practitioners attempting to design equitable interventions. This evaluation deliberately challenges the prevalent miscalculation that simply deploying technological tools automatically generates cognitive progress, reinforcing the position that structured instructional design must remain the central determinant of academic success.

Examining this interaction is particularly critical within the context of an Islamic boarding school locally known as a pesantren. Historically, pesantren environments rely heavily on traditional, highly structured, and teacher centric pedagogies. Introducing a student centered pedagogical deep learning approach supported by digital competencies in this specific environment provides a critical theoretical test of the intervention adaptability and its effectiveness in bridging traditional educational settings with modern competence demands (Ahmad et al., 2026; Talib et al., 2026). Therefore, this study investigates the effect of a pedagogical deep learning approach on students mathematical literacy while examining digital literacy as a continuous moderating variable (Cohen et al., 2017; Creswell & Creswell, 2018). Based on the theoretical framework, the following explicit hypotheses are proposed:

1. Hypothesis 1 (Main Effect of Instructional Approach): There is a significant difference in students' mathematical literacy improvement between the group receiving the pedagogical deep learning approach and the group receiving conventional instruction.
2. Hypothesis 2 (Main Effect of Digital Literacy): There is a significant main effect of students' continuous digital literacy competency on their mathematical literacy improvement.
3. Hypothesis 3 (Interaction/Moderation Effect): There is a significant interaction effect between the instructional approach and continuous digital literacy in predicting students' mathematical literacy improvement.

METHOD

Research Type or Design

A quantitative methodology was executed through a non-equivalent control group architecture incorporating pre-intervention and post-intervention measurements (Cohen et al., 2017; Creswell & Creswell, 2018). The fundamental aim of this structural design was to assess the influence of pedagogical deep learning strategies on mathematical literacy outcomes, while simultaneously investigating the moderating function of digital competency measured as a continuous metric. In accordance with rigorous statistical practices for moderation analysis, the research utilized a continuous interaction model to prevent the loss of data variance associated with artificial dichotomization. The independent variable was the instructional approach, which was categorized into pedagogical deep learning and conventional instruction. The dependent variable was the students mathematical literacy performance, measured before and after the educational intervention. Digital literacy served as the continuous moderator to determine whether the effectiveness of the instructional approach varied systematically across different levels of students technological competencies.

A methodological limitation inherent in this quasi-experimental design concerns the assignment of the educational treatment at the class level rather than at the individual student level. Because the intervention was administered to two intact classes due to strict administrative regulations at the participating educational institution, the treatment effects may be confounded with pre-existing class level characteristics. Consequently, the assumption of independent student level observations is partially compromised, as students within the same classroom share a common learning environment and peer dynamics. To mitigate this structural limitation and strengthen the validity of the inferences, the study established baseline equivalence by analyzing the pretest mathematical literacy scores of both groups prior to the intervention. Furthermore, an Analysis of Covariance (ANCOVA) was utilized during the data analysis phase. By assigning the pretest scores as a covariate, the statistical model effectively

controlled for initial differences in students mathematical abilities, thereby mathematically isolating the actual effect of the pedagogical intervention from baseline classroom disparities.

Participant, Sample, or Subject

The study was conducted during the second semester of the 2025/2026 academic year at SMA Pesantren Unggul Al Bayan, Sukabumi, Indonesia. The target population consisted of 128 Grade XI students distributed across four intact classes. From this population, two classes were selected using a cluster sampling technique to serve as the research sample (Cohen et al., 2017; Creswell & Creswell, 2018). One class was randomly assigned as the experimental group, which received instruction based on the pedagogical deep learning approach. The other class functioned as the control group, receiving conventional teacher centered instruction.

The initial sample comprised 63 students, with 32 students in the experimental group and 31 students in the control group. However, a rigorous data screening process revealed an extreme anomaly within the control group where one student recorded a posttest score of absolute zero due to absence during the final test administration. To preserve the statistical integrity of the analysis and prevent severe distortions in the variance and mean calculations, this specific case was excluded using listwise deletion. Consequently, the final sample size utilized for the statistical analysis was 62 students, comprising 32 students in the experimental group and 30 students in the control group.

To address the methodological constraints of utilizing intact classes and to ensure that the treatment effects were not confounded by prior mathematical abilities, baseline equivalence was rigorously established before the intervention. Both groups completed a comprehensive mathematical literacy pretest. The statistical summary of the baseline equivalence test is presented in Table 1.

Table 1. Baseline Equivalence of Pretest Mathematical Literacy Scores

Group	N	Mean	SD	t	df	p
Experimental	32	61.19	14.49	1.12	60	0.26
Control	30	57.20	13.44			

As shown in Table 1, an independent samples t-test revealed no significant difference in the pretest scores between the experimental group and the control group ($p > 0.05$). This empirical evidence confirms that both classes possessed an equivalent level of mathematical literacy prior to the administration of the instructional treatments. Establishing this baseline equivalence is a critical methodological step, as it provides a reliable foundation to attribute any subsequent differences in the posttest outcomes directly to the pedagogical deep learning intervention rather than to pre existing cognitive disparities among the student cohorts.

Instrument and Procedure

Data were collected using two primary instruments: a mathematical literacy test and a digital literacy questionnaire. Both instruments were subjected to rigorous validation processes prior to administration.

Mathematical Literacy Test Students'

Mathematical literacy was assessed using a written essay test comprising four contextual problems focused on Descriptive Statistics. The test was designed in strict alignment with the PISA 2022 framework, encompassing the core cognitive processes of formulating, employing, and interpreting mathematics in real-world contexts. To ensure content validity, the instrument was evaluated by a panel of two expert validators, both holding doctoral degrees in mathematics education, who assessed the construct relevance, context authenticity, and cognitive demand of each item. Because the students' written reasoning required qualitative interpretation, scoring subjectivity was mitigated by employing two independent raters (the classroom teacher and the primary researcher) using a standardized rubric. The inter-rater reliability was calculated using Cohen's Kappa, yielding an excellent agreement coefficient of

$\kappa = 0.88$. Any scoring discrepancies were resolved through consensus discussion. The comprehensive mapping of the test items, including their respective domains, contexts, PISA processes, maximum scores, and scoring rubrics, is detailed in Table 3.

Table 2. PISA-Based Mathematical Literacy Test Mapping and Scoring Rubric

Item	Content Domain	Context	PISA Process	Difficulty	Max Score	Scoring Rubric (0 to Max Score)
1	Uncertainty and Data	Societal	**Formulate:** Translate real-world data distribution into mathematical representation.	Moderate	3	**0:** No response or entirely incorrect. **1:** Partial formulation with missing variables. **2:** Accurate mathematical representation without justification. **3:** Flawless translation into mathematical models with complete logical reasoning.
2	Uncertainty and Data	Scientific	**Employ**: Apply algorithms to determine Mean and Interquartile Range (IQR).	Moderate	4	**0:** No response. **1:** Identifies formula but fails computation. **2:** Computes mean/IQR with minor arithmetic errors. **3:** Accurate calculation but lacks step-by-step logic. **4:** Precise execution of strategies to find the exact mathematical solution.
3	Uncertainty and Data	Occupational	**Employ:** Design and apply strategies to identify outliers using IQR boundaries.	High	4	(Same as Item 2): Focuses on the precise execution of complex statistical procedures to find outliers.
4	Uncertainty and Data	Societal	**Interpret:** Evaluate data stability and interpret the impact of outliers on the mean.	High	3	**0**: No response. **1**: Weak or illogical argument regarding data stability. **2**: Correct conclusion but insufficient contextual justification. **3**: Robust explanation detailing why the mathematical result makes sense in the given real-world context.

Digital Literacy Questionnaire

Digital literacy was measured using a 45-item self-report questionnaire. The instrument was theoretically grounded in Gilster's digital literacy framework and adapted from validated scales within the Indonesian educational context. Students responded using a 5-point Likert

scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The construct validity of the instrument was established through expert evaluation by two university specialists in educational technology, who verified the items' relevance to four operational dimensions: (1) Communication and Digital Content Sharing, (2) Digital Content Creation, (3) Access and Utilization of Content, and (4) Security in Digital Device Usage. The overall internal consistency of the questionnaire was excellent, with a Cronbach's alpha of $\alpha = 0.915$. Furthermore, reliability analyses conducted by dimension confirmed acceptable to strong internal consistency across all subscales: Communication and Digital Content Sharing ($\alpha = 0.75$), Digital Content Creation ($\alpha = 0.79$), Access and Utilization of Content ($\alpha = 0.81$), and Security in Digital Device Usage ($\alpha = 0.85$). As requested by the methodological guidelines, the digital literacy scores were computed as continuous variables (ranging theoretically from 45 to 225) to be utilized as a continuous moderator in the statistical analysis, rather than being artificially dichotomized into categorical groups.

To address potential threats to internal validity and ensure that the observed outcomes were attributable to the instructional approach rather than extraneous classroom differences, stringent intervention fidelity protocols were implemented. Both the experimental and control groups received instruction over six meetings, with each meeting lasting 80 minutes (2 × 40 minutes). To eliminate teacher-related confounding variables, the same mathematics teacher instructed both groups across all sessions. Instructional fidelity was monitored throughout the intervention by independent observers using a standardized observation checklist to guarantee that the deep learning principles were consistently applied in the experimental group, and strictly withheld from the control group. In the experimental group, instruction was guided by the pedagogical deep learning approach, operationalized through the Problem-Based Learning (PBL) model. The learning environment was designed to foster active student engagement through three core principles: *meaningful learning* (connecting statistical concepts to real-life contexts such as student test scores and heights), *mindful learning* (encouraging continuous metacognitive reflection and critical awareness of data functions), and *joyful learning* (facilitating collaborative exploration and interactive presentations using digital tools). The teacher acted as a facilitator, providing contextual stimuli and triggering questions, while students collaboratively formulated problems, processed data, and interpreted mathematical results. Conversely, the control group received conventional teacher-centered instruction. During these sessions, the teacher directly explained the statistical concepts, provided step-by-step formula derivations on the whiteboard, and demonstrated sample problem solutions. Students in the control group predominantly engaged in passive note-taking and individual practice of routine, non-contextual textbook exercises. The conventional instruction strictly excluded collaborative problem-solving, real-world contextualization, and structured metacognitive reflection. A detailed comparative breakdown of the instructional procedures for all six meetings is presented in Table 3.

Table 3. Detailed Intervention Protocol for Experimental and Control Groups

Meeting & Duration	Topic & Learning Objective	Deep Learning Activities in Experimental	Experimental	Control
Meeting 1	**Mean and Mode:** Calculate and interpret mean and mode in data-based problems.	**Meaningful:** Analyzing contextual student test scores. **Mindful:** Realizing the importance of data representation in daily life. **Joyful:** Active group observation and data exploration.	**Teacher:** Provides contextual stimuli; facilitates group discussion. **Student:** Formulates questions; calculates mean/mode	Teacher directly explains mean/mode formulas. Students individually complete routine numerical

Meeting & Duration	Topic & Learning Objective	Deep Learning Activities in Experimental	Experimental	Control
			collaboratively; presents findings.	calculation exercises.
Meeting 2	**Median and Quartiles:** Determine median and quartiles (Q_1, Q_2, Q_3); interpret data position.	**Meaningful:** Utilizing real-world student height data. **Mindful:** Understanding the positional division of data. **Joyful:** Interactive data sorting and peer discussion.	**Teacher:** Presents raw contextual data; asks triggering questions on data position. **Student:** Sorts data logically; calculates median/quartiles ; draws conclusions.	Teacher writes median/quartile steps on the board. Students memorize the procedures and solve standard textbook problems.
Meeting 3	**Range and Mean Deviation:** Determine range and mean deviation; interpret data spread.	**Meaningful:** Understanding the concept of data stability using student scores. **Mindful:** Recognizing the existence of data variation. **Joyful:** Engaging in collaborative calculations.	**Teacher:** Guides students to observe maximum/minimum values; reinforces concepts. **Student:** Identifies information; calculates deviation; interprets the spread of data.	Teacher defines range and deviation. Students practice calculating deviation from abstract number sets.
Meeting 4	**Variance and Standard Deviation:** Calculate and interpret variance and standard deviation.	**Meaningful:** Comparing the stability of two different groups of data (Class A vs. Class B). **Mindful:** Critically analyzing differences in data variations. **Joyful:** Comparative discussions and evaluating data stability.	**Teacher:** Presents comparative datasets; facilitates analytical discussions. **Student:** Computes variance/standard deviation; interprets which class data is more stable.	Teacher demonstrates standard deviation formulas. Students independently calculate variance from given uncontextualized data.
Meeting 5	**Deciles and Percentiles:** Determine and interpret data rank positions.	**Meaningful:** Applying concepts to real-life student rankings. **Mindful:** Reflecting on specific rank positions within a larger group. **Joyful:** Active exploration of percentage-based data positions.	**Teacher:** Connects decile/percentile concepts to everyday rankings. **Student:** Sorts data; calculates D_n and P_n ; evaluates data positioning.	Teacher explains decile/percentile formulas. Students apply formulas mechanically without ranking contexts.

Meeting & Duration	Topic & Learning Objective	Deep Learning Activities in Experimental	Experimental	Control
Meeting 6	**Outliers:** Identify outliers using IQR and interpret their impact.	**Meaningful:** Analyzing the impact of extreme values (e.g., a score of 120) on overall averages. **Mindful:** Critically evaluating abnormal/deviant data points. **Joyful:** Intrigue and debate generated by identifying unusual data.	**Teacher:** Introduces data with extreme anomalies; explains IQR boundaries. **Student:** Computes IQR; identifies outliers; evaluates the impact of outliers on data accuracy.	Teacher defines outliers theoretically. Students calculate Q_1, Q_3, and IQR to find outliers without discussing the real-world impact.

Data Analysis

Statistical processing was conducted via SPSS, encompassing both descriptive and inferential phases. Initial calculations provided means and standard deviations to outline the distribution of assessment scores and digital competency levels. Prior to evaluating the primary hypotheses, preliminary statistical assumptions were rigorously verified. To directly address the research hypotheses and evaluate the moderating effect of digital literacy, an Analysis of Covariance (ANCOVA) was employed. Aligning with rigorous methodological standards, digital literacy was maintained as a continuous variable rather than being artificially dichotomized, preventing the degradation of statistical variance. The instructional approach served as the independent categorical variable, digital literacy as the continuous moderator, and the posttest mathematical literacy score as the dependent variable. The pretest score was entered as a covariate to mathematically control for initial cognitive differences among the students. The interaction term (Instructional Approach × Digital Literacy) was specifically analyzed to determine the moderation effect. To ensure a meaningful interpretation of the main effects within the ANCOVA model, the continuous moderating variable (digital literacy) was mean-centered prior to the analysis. This transformation guarantees that the evaluated main effect of the instructional approach represents group differences at the average level of students' digital literacy. All inferential tests were evaluated at a significance level of $\alpha = 0.05$.

RESULTS AND DISCUSSION

The Impact of Pedagogical Deep Learning on Mathematical Literacy

Initial statistical summaries detailing the enhancement of mathematical literacy, quantified via the N-Gain metric, reveal observable variances between the differing educational conditions. Before executing inferential procedures, the prerequisite conditions for data normality were systematically verified. Adhering to robust statistical guidelines for factorial designs, normality was assessed based on the model residuals rather than raw group distributions. Given the adequate and balanced sample sizes across both instructional groups, the general linear model remains robust against minor deviations from strict normality. The complete descriptive statistics are presented in Table 4.

Table 4. Descriptive Statistics of Mathematical and Digital Literacy

Variable	Experimental Group (n = 32) Mean	SD	Control Group (n = 30) Mean	SD
Pretest Mathematical Literacy	61.19	14.49	57.20	13.44
Posttest Mathematical Literacy	86.41	7.83	70.77	11.30
Digital Literacy	184.84	20.20	175.47	20.07
N-Gain	0.60	0.22	0.27	0.32

As presented in Table 4, the experimental and control groups showed relatively comparable levels of mathematical literacy before the intervention. The experimental group obtained a pretest mean score of 61.19 (SD = 14.49), while the control group achieved a mean score of 57.20 (SD = 13.44). Following the instructional intervention, a more pronounced difference emerged between the two groups. The experimental group reached a posttest mean score of 86.41 (SD = 7.83), whereas the control group obtained a mean score of 70.77 (SD = 11.30). The increase in the experimental group was therefore greater, accompanied by a lower posttest standard deviation, indicating that students' mathematical literacy scores became not only higher but also more homogeneous after participating in the pedagogical deep learning approach.

A similar pattern was observed in digital literacy. The experimental group recorded a higher mean digital literacy score of 184.84 (SD = 20.20) compared with 175.47 (SD = 20.07) in the control group. Although the standard deviations were nearly identical, the higher mean score in the experimental group suggests that students exposed to the pedagogical deep learning approach demonstrated a stronger overall level of digital literacy than those receiving conventional instruction.

The N-Gain results further illustrate the difference in mathematical literacy improvement between the two groups. The experimental group achieved a mean N-Gain of 0.60 (SD = 0.22), while the control group obtained a mean N-Gain of 0.27 (SD = 0.32). Thus, the experimental group demonstrated more than twice the average normalized improvement observed in the control group. Moreover, the lower standard deviation of the experimental group indicates that improvement was relatively more consistent among students, whereas the larger standard deviation in the control group reflects greater variability in learning gains.

Taken together, these descriptive findings indicate that students who participated in the pedagogical deep learning approach demonstrated higher post-intervention mathematical literacy, higher digital literacy, and greater normalized improvement than students receiving conventional instruction. The pattern is consistent with the principles of meaningful, mindful, and joyful learning embedded within the intervention. Meaningful learning supports students in connecting mathematical concepts with authentic contexts, while mindful learning promotes deliberate reflection, monitoring, and evaluation of problem-solving processes. Joyful learning can further support active engagement and sustained participation in learning activities. These characteristics may contribute to stronger conceptual understanding and the ability to formulate, employ, and interpret mathematics in real-world situations, which are central to contemporary mathematical literacy frameworks (OECD, 2023; Siregar et al., 2025; Siregar et al., 2026; Wahyuningsih et al., 2026).

The Moderating Effect of Digital Literacy

Prior to evaluating the moderation dynamics through ANCOVA, the fundamental statistical assumptions were formally assessed. The Shapiro-Wilk test conducted on the model residuals indicated a deviation from strict normality ($W = 0.911, p < 0.001$). Similarly, Levene's test revealed heterogeneity of variances across the groups, $F(1,60) = 8.58, p = 0.005$. Furthermore, the examination of the homogeneity of regression slopes indicated a slight interaction between the instructional approach and the pretest covariate ($p = 0.034$). Although the dataset deviated from these strict parametric assumptions, standard ANCOVA procedures are recognized in statistical literature as highly robust against violations of normality and homogeneity when group sample sizes are balanced and approximately equal, as is the case in this study ($n = 32$ and $n = 30$) (Field, 2018; Howell, 2012). Consequently, the analysis proceeded with the standard univariate model to maintain interpretability while carefully acknowledging the data distribution properties.

A univariate Analysis of Covariance was implemented to examine the principal hypotheses and assess the moderation dynamics, intentionally avoiding the artificial categorization of the moderating factor. Within this statistical model, final mathematical

literacy achievements functioned as the primary outcome. Initial pretest measurements were integrated as a covariate to statistically neutralize pre-existing cognitive variations, while continuous digital competency levels and the designated pedagogical methods operated as the predictive variables. The summary of the ANCOVA results is detailed in Table 5.

Table 5. ANCOVA Results for Tests of Between-Subjects Effects (Dependent Variable: Posttest)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	4610.049	4	1152.512	13.742	.000	.491
Intercept	14232.782	1	14232.782	169.709	.000	.748
Class (Instructional Approach)	3407.976	1	3407.976	40.636	.000	.416
Pretest (Covariate)	354.991	1	354.991	4.233	.044	.069
Lit_Dig_ Center (Moderator)	72.788	1	72.788	.868	.355	.015
Class * Lit_Dig_ Center	300.667	1	300.667	3.585	.063	.059
Error	4780.338	57	83.866			
Total	394754.000	62				
Corrected Total	9390.387	61				

The computational findings presented in Table 5 indicate that the initial covariate successfully accounted for starting cognitive disparities, $F(1,57) = 4.233, p = 0.044$, Partial Eta Squared $= 0.069$. By utilizing the mean-centered digital literacy score, the model accurately evaluated the main effect of the instructional approach. The analysis revealed a highly significant main effect for the pedagogical approach on posttest outcomes, $F(1,57) = 40.636, p < 0.001$, Partial Eta Squared $= 0.416$, indicating that at the average level of digital literacy, students in the deep learning environment significantly outperformed those in the conventional setting. Regarding the moderation inquiry, the combined interaction involving the teaching methodology and the mean-centered digital proficiency metric (Class * Lit_Dig_Center) resulted in an $F(1,57) = 3.585, p = 0.063$, Partial Eta Squared $= 0.059$. Because the p-value marginally exceeds the 0.05 threshold, there is insufficient statistical evidence to confirm a significant interaction. This statistical outcome indicates that the pedagogical deep learning approach maintained its efficacy across varying levels of digital literacy within this specific sample. Consequently, separate subgroup comparisons were deliberately excluded to prevent methodological overreach. To visually represent these findings, a grouped scatter plot with regression fit lines was generated.

The non-significant interaction term indicates that the pedagogical deep learning approach maintained a consistent trajectory of effectiveness across varying levels of students' initial technological readiness. This finding offers a valuable pedagogical implication. It indicates that the success of the instructional intervention was driven primarily by the quality of the pedagogical practices rather than the baseline technological competencies of the students (Siregar et al., 2025; Wahyuningsih et al., 2026). This is further evidenced by the remarkably low R^2 values observed in the regression models (0.014 for the experimental group and 0.119 for the control group). These minimal variance percentages visually and statistically corroborate that students' technological proficiency exerted almost negligible influence on their capacity to absorb and interpret complex mathematical problems. The deep learning environment functioned as an inclusive instructional framework. The structured scaffolding and collaborative peer discourse effectively supported all students, ensuring that those with lower digital literacy were not systematically disadvantaged. This interpretation reinforces recent educational consensus emphasizing that while digital environments offer immense potential, the pedagogical integration of technology must prioritize structured, student-centered frameworks to ensure instructional equity and active meaning-making, particularly in conventional or low-resource contexts (Daulay & Nurfitriani, 2026; Syahruddin & Agus, 2026; Zoubir et al., 2026). Consequently, Hypothesis 3 is rejected. This confirms that digital literacy

in this specific context functioned as an ancillary competency rather than a primary determinant or a significant moderator of mathematical literacy development.

The Main Effect of Digital Competency on Mathematical Outcomes

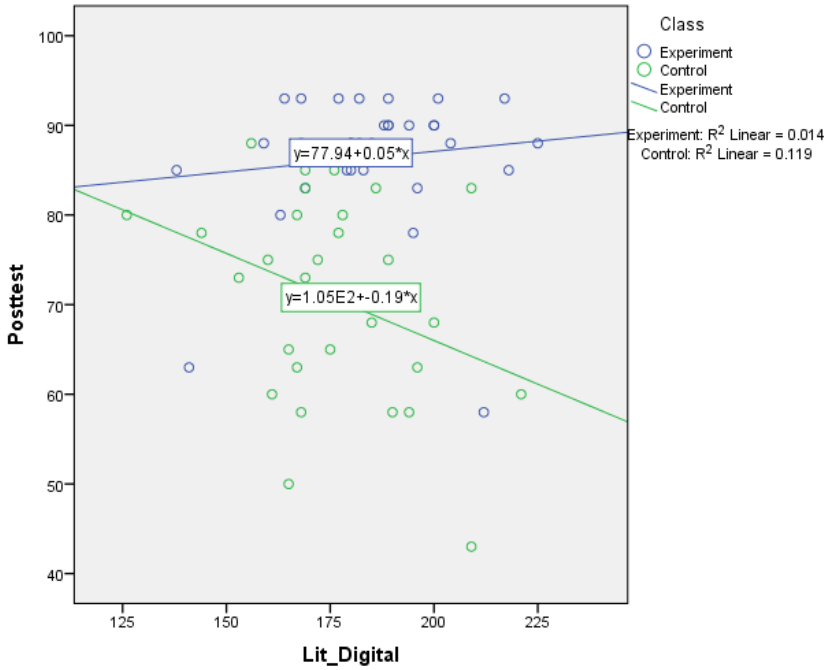


Figure 1. Interaction plot of instructional approach and continuous digital literacy predicting mathematical literacy

Graphical representation in Figure 1 demonstrates that the regression trajectories for both the treatment and conventional cohorts maintain clear separation without intersection along the entire spectrum of digital competency scores. This persistent vertical gap between the superior experimental trajectory and the lower conventional trajectory provides visual validation of the primary pedagogical effect. The absence of a cross-over interaction further corroborates the ANCOVA results, demonstrating that students in the deep learning environment consistently outperformed their peers in the conventional setting regardless of their initial digital competencies. Furthermore, the extremely low R^2 values (0.014 for the experimental group and 0.119 for the control group) visually validate this finding, indicating that students' baseline digital literacy accounted for very little variance in their final mathematical literacy outcomes.

A central theoretical objective of this investigation was to determine whether students' continuous digital literacy competency exerted a main effect on mathematical literacy improvement. The univariate ANCOVA results provided insufficient statistical evidence to support this proposition. The absence of a significant main effect suggests that mere proficiency in utilizing digital devices does not automatically translate into stronger mathematical reasoning abilities. This phenomenon can be explained by the nature of students' digital habits and the distinction between actual digital competence and everyday usage frequency (Caponera et al., 2026; Susanta et al., 2025). Students frequently exhibit differing patterns of digital behavior, utilizing technology primarily for social communication or entertainment rather than for deep mathematical exploration or complex data modeling. This finding is highly consistent with previous assessments establishing that mathematical performance is influenced by learning-related factors, metacognitive strategies, and structured inquiry rather than pure technological access (Chen & Xiao, 2024; Li & Chen, 2026). Consequently, Hypothesis 2 is rejected.

Cognitive Trajectories in Mathematical Reasoning

To complement the quantitative findings and illustrate the distinct cognitive trajectories between the two instructional settings, an analysis of students' written artifacts was conducted. Addressing methodological best practices, a purposive sampling technique was employed to select eight representative student posttest worksheets (four from the experimental group and four from the control group). These artifacts were specifically chosen to reflect the typical reasoning patterns and common problem-solving behaviors observed within each group. The summary of this artifact analysis is categorized by dominant reasoning patterns, frequent cognitive errors, and representative evidentiary quotes in Table 6.

Table 6. Summary of Students' Mathematical Reasoning

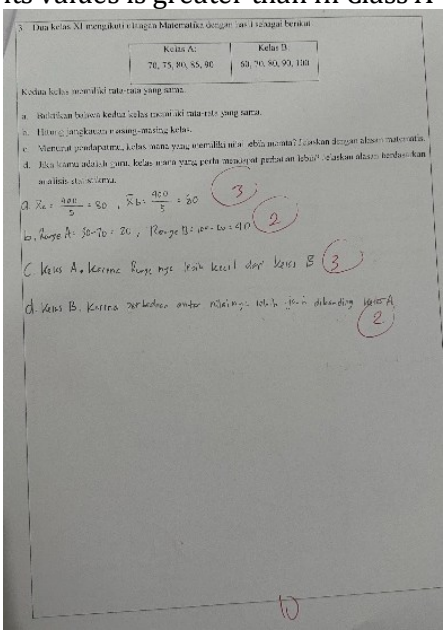
Group	Analyzed Responses (n)	Dominant Reasoning Pattern	Frequent Error / Limitation	Representative Evidence (Student Artifacts)
Experimental	4	Conceptual and Strategic: Students systematically applied advanced statistical tools (e.g., Assumed Mean, Interquartile Range) and explicitly evaluated data spread. They successfully linked mathematical results to real-world contexts.	Minor arithmetic slips; occasional informal phrasing when formulating real-world policy recommendations.	"The exact choice is the median, because the mean becomes inaccurate due to the presence of the outlier (150)." (Student successfully evaluating the resistance of statistical measures).
Control	4	Procedural and Mechanical: Students demonstrated competence in basic arithmetic operations and standard formula execution but treated numbers as isolated values.	Interpretative Failure: Inability to select appropriate statistical measures when extreme values (outliers) are present. Tendency to leave contextual reasoning questions blank.	When asked to choose a better statistical measure due to an outlier, a student irrelevantly drew a bar chart. Another student left the interpretation section completely blank.

The analytical summary in Table 6 delineates a marked divergence in mathematical reasoning between the two cohorts. Experimental group students predominantly exhibited conceptual and strategic reasoning. They systematically applied advanced statistical tools and successfully linked mathematical results to real-world contexts. Conversely, control group students demonstrated procedural and mechanical reasoning. While capable of executing basic arithmetic, they frequently failed to interpret data anomalies or select appropriate statistical measures when extreme values were present. This divergence is explicitly captured in the students' written responses.

Table 7. Results Written post-test: control class (left), experimental class (right)

Control Group Student	Experimental Group Student
Control: **Question 3**: a. $\bar{x}a = 400/5 = 80$, $\bar{x}b = 400/5 = 80$	Experimental: **Question 3**: a. $\bar{x}a = 80$, $\bar{x}b = 80$ $\bar{x}a = 80$, $\bar{x}b = 80$ "Both averages are the same."

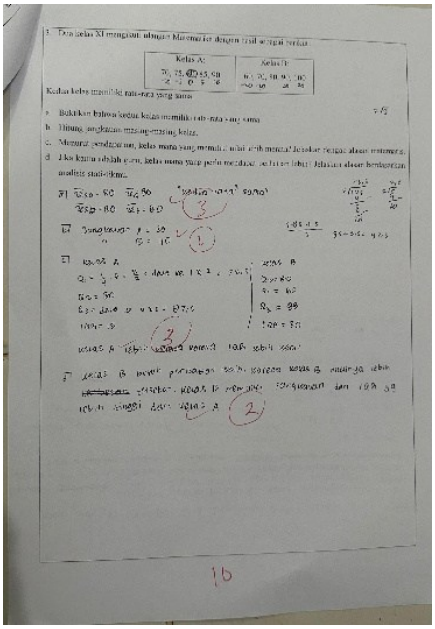
b. Range A = 90-70 = 20, Range B = 100 – 60 = 40
c. Class A, because its range is smaller than Class B
d. Class B, because the variation between its values is greater than in Class A



Question 4:

a. 465/7 = 66.42
b. Not quite right, because only Saturday's delivery has a very high value. For other days, it is already stable with a difference of 5 packages.
c. [Draws a bar chart showing "a significant height difference" accompanied by the handwritten note: "Bar chart. A significant difference in height."]
d. would suggest to reinvestigate the package delivery on Saturday and Sunday. If it is indeed like that, Saturday should deliver 65 packages and Sunday should deliver 70 packages.

b. Range A = 20. Range B = 40
c. Class A.
Q1 = 1/4 . 6 = 3/2 Data 1 & 2 = 72.5
Q2 = 80
Q3 = Data 4 & 5 = 87.5
IQR = 15
Class B
Q2 = 80
Q1 = 65
Q3 = 95
IQR = 30
Class A is more evenly distributed because its IQR is smaller.
d. Class B needs more attention, because class B's scores are more scattered. Class B has a higher range and IQR than class A (IQR A = 15, IQR B = 30)



Question 4:

a. $\bar{x}_s = 55 \quad \bar{x} = 55 + \frac{80}{7} \approx 66.4$
b. Q2 = 55
Q1 = 45
Q3 = 65
IQR = 20
BB = 15
BA = 95
Median = 55
(Side notes on the right):
"150 is an outlier because it is greater than the upper bound" "without the outlier, the mean wouldn't be 66.4" "the more appropriate figure to use for the average is the median (55)"
c. The appropriate statistical measure is can determine outliers and can make boxplots. The right choice is the median, because the mean is inaccurate with the presence of

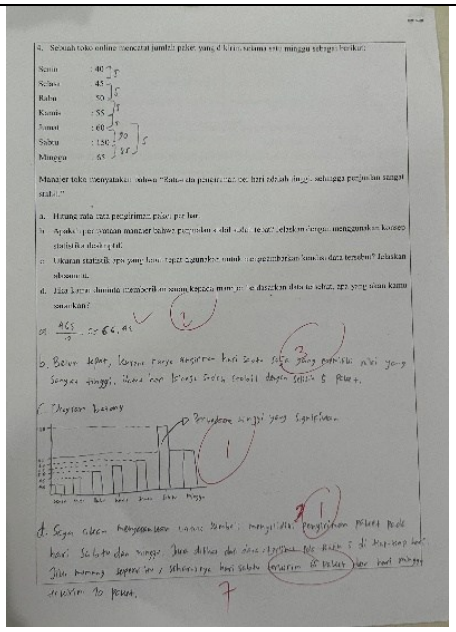
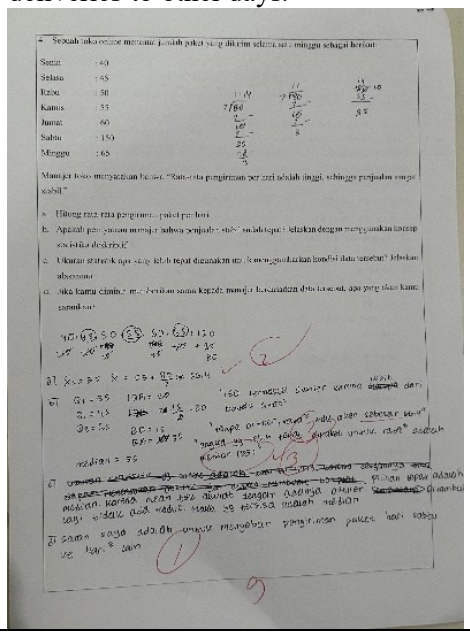
	outliers. Meanwhile Furthermore, there is no mode. Therefore, what remains is the median. d. My suggestion is to spread Saturday's package deliveries to other days. 

Table 7 provides direct documentary evidence of the cognitive disparities highlighted in Table 6. The left panel displays a representative worksheet from a control group student, revealing a strong reliance on procedural intuition. When prompted to evaluate a statistical outlier, the student irrelevantly constructed a bar chart and provided superficial contextual recommendations without sound mathematical justification. In contrast, the right panel illustrates the response of an experimental group student who engaged in rigorous statistical evaluation. This student successfully identified the outlier, explicitly noted its distorting effect on the mean calculation, and provided a mathematically robust argument for selecting the median as a more accurate measure of central tendency. These artifacts substantiate the quantitative data, confirming that the deep learning approach facilitates higher-order interpretative skills beyond routine computation.

This cognitive transition is explicitly corroborated by the qualitative artifact analysis. Control group students primarily demonstrated procedural and mechanical reasoning. While they successfully executed basic arithmetic, they frequently failed to interpret extreme values and could not connect statistical outputs to real-world implications. In contrast, experimental students exhibited conceptual and strategic reasoning by successfully utilizing advanced statistical tools to make sense of realistic scenarios. This finding strongly aligns with previous studies reporting that deep learning-oriented environments and flipped instructional models effectively promote meaningful understanding and autonomous cognitive development (Duan et al. 2024; Fernández-Araque et al., 2026; Zheng et al. 2026). Furthermore, the observed transition from procedural execution to multivariable evaluation supports the theoretical stance that advanced mathematical literacy requires robust logical-mathematical processing and a psychologically safe learning environment to transcend simple intuitive judgments (Aisiya & Suryanti, 2026;Siregar et al., 2026). The interactive nature of joyful learning also sustained student engagement throughout the complex problem-solving phases, corroborating assertions that reflective participation, technology-enhanced embodiment, and affective interactive factors are essential mechanisms for deeper mathematical understanding (Li et al., 2026; Liu et al., 2026; Singh et al., 2026; Yeung & Ng, 2023). Therefore, Hypothesis 1 is conclusively accepted, confirming that the pedagogical deep learning approach exerts a significant positive main effect on students' mathematical literacy compared to conventional instruction.

CONCLUSION

This study concludes that the pedagogical deep learning approach, operationalized through contextual student worksheets integrating meaningful, mindful, and joyful learning experiences, significantly improved students' mathematical literacy. The experimental class showed significantly higher gains under the implemented conditions, achieving a mean N-Gain of 0.60, compared to a mean N-Gain of 0.27 in the conventional instruction group. This empirical outcome indicates that structured, student-centered learning environments prioritizing conceptual meaning-making are highly effective in elevating mathematical competencies.

Furthermore, the statistical analysis revealed no statistically detectable moderation in this sample regarding students' continuous digital literacy. This non-significant interaction does not imply universal independence from digital literacy. Rather, it suggests that within this specific instructional context, the pedagogical quality of the deep learning approach maintained stable effectiveness across varying levels of student technological readiness. The analysis of student written artifacts supported these quantitative results. Experimental students demonstrated conceptual reasoning and advanced interpretation, whereas control students relied predominantly on procedural execution and failed to interpret real-world data anomalies. Ultimately, the findings suggest that mathematical literacy development is driven by active, self-regulated cognitive engagement rather than mere procedural repetition or baseline technological proficiency.

Despite these limitations, the study offers critical implications for mathematics education. It provides empirical evidence that mathematical literacy interventions must prioritize pedagogical depth over procedural drilling. Educational practitioners should focus on designing robust instructional frameworks that integrate real-world contexts and metacognitive reflection, rather than relying excessively on students' baseline digital competencies to drive academic achievement.

RECOMMENDATION

While the findings provide robust support for the pedagogical deep learning approach, several methodological limitations inherent to the quasi-experimental design must be explicitly acknowledged. First, strict institutional regulations necessitated the assignment of educational treatments at the intact-class level rather than via true individual randomization. Although baseline equivalence was established and ANCOVA was employed to statistically control for initial disparities, the potential confounding influence of pre-existing classroom dynamics cannot be entirely eliminated. Second, the intervention was conducted over a relatively short duration of six meetings within a single educational institution. While this duration was sufficient to observe acute pedagogical effects on descriptive statistics, it restricts the generalizability of the findings to broader educational settings or other mathematical domains. Third, the instructional delivery for both groups was executed by a single teacher, introducing the possibility of unconscious instructional bias.

Based on the empirical insights of this classroom inquiry, several pathways are proposed to reshape instructional practices in mathematics education. First, mathematics educators should actively transition away from conventional, teacher-centered instructional models. Educators should prioritize the deliberate design of reflective, student-centered learning environments by developing contextual materials that challenge students to critically investigate and evaluate mathematical concepts within authentic daily contexts. Second, the integration of digital technology within educational settings should be fundamentally repositioned. Rather than treating digital devices as direct determinants of learning success, schools should utilize technology as a supportive cognitive scaffold designed specifically to facilitate collaborative data visualization and active meaning-making.

To address the methodological boundaries of this study, future researchers are strongly encouraged to expand the current framework. Future work should prioritize replication across

multiple schools with more than one class per condition to reduce confounding class-level variables and increase statistical generalizability. Subsequent investigations should also consistently utilize continuous moderation analysis, incorporate strict treatment-fidelity measures throughout the intervention, and employ delayed posttests to evaluate the long-term cognitive sustainability of the mathematical literacy gains.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Muhamad Abdul Rohman	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Mohammad Syaifuddin						✓		✓		✓				
Reni Dwi Susanti		✓		✓		✓		✓	✓	✓	✓	✓		

CONFLICT OF INTEREST STATEMENT
Authors state no conflict of interest.

INFORMED CONSENT
We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL
The inquiry complied strictly with established ethical guidelines for educational research involving human participants. Institutional authorization was granted by the administration of SMA Pesantren Unggul Al Bayan preceding any data collection activities. Given the minor status of the subjects, robust ethical protocols were mandated. Formal written approval was collected from the legal guardians of all involved learners, ensuring complete transparency regarding the research objectives, instructional methods, and data utilization. Furthermore, written student assent was explicitly collected to ensure their voluntary participation. All participants were thoroughly informed of their right to withdraw from the research at any time without facing any academic penalties or negative consequences. To protect participant privacy and maintain confidentiality, all collected data were strictly anonymized, securely stored, and exclusively utilized for academic research purposes.

DATA AVAILABILITY
The data that support the findings of this study are available from the corresponding author, MAR, upon reasonable request. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to ethical restrictions.

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