BULETIN LITERASI BUDAYA SEKOLAH
journal homepage – https://journals2.ums.ac.id/index.php/blbs
Vol. 8 No. 1 July 2026

A Comparative Analysis of Coding and Artificial Intelligence Learning Implementation on Teacher Competence, Student Learning Interest, and Motivation in Elementary Schools

Doi: 10.23917/blbs.v8i1.17643

Hendra Wahyudi[1*], Hafiz Hidayata[1], and Ismira[1]
*Corresponding author: hendrawahyudispsd20@gmail.com

[1]*Adzkia University, Padang, Indonesia*

ARTICLE INFO

Keywords:
Artificial intelligence
Coding learning
Learning interest
Learning motivation
Teacher competence

ABSTRACT

This study aims to analyze the comparative differences and effects of coding and artificial intelligence (AI) learning implementation on teacher competence, student learning interest, and student learning motivation at elementary schools in Kayu Aro Barat District, Kerinci Regency. A quantitative comparative explanatory (ex post facto) design was employed. The population consisted of all Grade V teachers and students across 17 elementary schools based on data from the Kerinci Regency Education Office (2024). Using proportionate stratified random sampling, eight schools were selected—four implementing coding and AI (experimental group) and four not implementing it (control group)—involving 8 teachers and 120 fifth-grade students. Data were collected through a structured Likert-scale questionnaire (1–5), observation, documentation, and semi-structured interviews. Analysis employed MANOVA (Y2 and Y3), independent sample t-test, and multiple linear regression. Results showed: (1) significant differences in teacher competence ($t = 7.215$; $p = .000$; mean diff. = 13.75), learning interest ($t = 9.123$; $p = .000$; mean diff. = 12.20), and learning motivation ($t = 8.764$; $p = .000$; mean diff. = 12.10); (2) significant positive effects on learning interest ($\beta = 0.748$; $R^2 = 0.560$) and learning motivation ($\beta = 0.751$; $R^2 = 0.564$); and (3) simultaneous multivariate effects on student learning interest and motivation (Wilks' $\Lambda = 0.538$; $F = 50.20$; $df = 2, 117$; $p = .000$). These findings confirm that structured coding and AI implementation substantially enhances elementary school learning quality in Kayu Aro Barat District.

INTRODUCTION

The rapid advancement of digital technology in the 21st century has fundamentally reshaped educational priorities worldwide. International bodies, including UNESCO and the OECD, consistently call upon educational systems to equip students with competencies beyond traditional literacy, among them computational thinking, data fluency, and the ability to interact meaningfully with artificial intelligence (Maleni et al., 2025). Indonesia has responded to this imperative through the Merdeka Curriculum, which explicitly mandates integrating coding and artificial intelligence (AI) into classroom practice from the elementary level onward (Suharyo et al., 2024; Prihatin, 2025). This policy shift reflects a broader recognition that early exposure to coding and AI is no longer a privilege of technology-rich environments, but a foundational preparation for all learners in a digitally interconnected society.

However, the empirical reality in Indonesia tells a more complex story. National data indicate that the country's digital literacy index in 2023 was only 3.54 out of 5 (moderate category), suggesting that technology integration in learning remains far from optimal (Muttaqin & Rahmatillah, 2026; Nasori et al., 2024). PISA results further reveal that Indonesian students' critical thinking and problem-solving abilities consistently fall below the OECD member-country average competencies intrinsically tied to computational and digital skill development (Griyanora & Widodo, 2026). At the teacher level, many elementary educators report limited understanding of coding and AI concepts, and readiness for technology-based curricula remains only moderate in many regions (Sofiyati & Jasiah, 2026; Arahman & Isdaryanti, 2026). Together, these data point to a persistent gap between policy aspiration and classroom reality.

Theoretical and empirical scholarship offers a foundation for understanding why bridging this gap matters. The TPACK framework establishes that teacher competence in the digital era grows most effectively through sustained, active engagement with technology in instruction—not through passive exposure alone (Mishra et al., 2022). At the student level, Self-Determination Theory (Ryan & Deci, 2020) and the ARCS motivational model (Keller, 2009) both predict that well-designed technology-based learning environments can simultaneously activate student interest, confidence, and intrinsic motivation. A growing body of evidence supports these theoretical predictions: studies have confirmed that structured coding and AI programs improve teacher digital competence (Budiarti et al., 2025; Pratama et al., 2025), enhance student learning interest and creativity (Tang et al., 2021; Wati et al., 2025), and transform teacher practice across disciplines (Imawati et al., 2026). This convergence of theory and evidence provides a compelling rationale for examining coding and AI implementation as a lever for systemic educational improvement.

However, significant gaps remain in the existing literature. Most studies predominantly examine a single outcome, either teacher competence or student motivation, in isolation, without capturing the simultaneous, interrelated effects across multiple dimensions. Moreover, the vast majority are set in urban areas with relatively complete technological infrastructure, leaving schools in semi-urban and rural regions largely undocumented (Andani & Arifin, 2026; Mardianti & Widodo, 2026). Whether the benefits of coding and AI implementation are equally achievable in resource-constrained settings and whether they operate simultaneously across teacher and student outcomes remain open empirical questions. This study addresses that question directly by simultaneously examining three outcome variables: teacher competence (Y1), student learning interest (Y2), and student learning motivation (Y3) through a combination of comparative and multivariate analyses, applied in a regional context not previously studied.

That context is Kayu Aro Barat District, Kerinci Regency, Jambi Province, a highland area characterized by diverse socioeconomic conditions and markedly uneven access to technology across schools. Based on data from the Kerinci Regency Education Office (2024) and field observations, a clear disparity exists among the district's 17 elementary schools. Schools that have implemented coding and AI learning generally possess adequate digital infrastructure, computers or laptops, internet connectivity, trained teachers, and curricula aligned with the Merdeka Curriculum's technology requirements. In contrast, schools without such implementation remain dependent on textbook-based instruction, with minimal interactive media and teachers who report limited familiarity with coding and AI. This within-district disparity creates a naturally occurring comparative condition that is both empirically meaningful and methodologically appropriate for an ex post facto design.

This convergence of theoretical grounding, empirical evidence, identified literature gaps, and contextual urgency motivates the present study. If coding and AI implementation produce meaningful, simultaneous improvements in teacher competence and student affective outcomes even in infrastructure-limited regional settings, the implications for equity-oriented educational policy are substantial. Conversely, if no significant differences are observed, this would equally signal that implementation without adequate support systems is insufficient itself, a critical finding for policymakers. Accordingly, this study aims to analyze the comparative differences and effects of coding and AI learning implementation on teacher competence (Y1), student learning interest (Y2), and student learning motivation (Y3) at elementary schools in Kayu Aro Barat District, Kerinci Regency, using a multivariate approach that captures these outcomes in their full, interrelated complexity.

LITERATURE REVIEW

Coding Education

Coding education in elementary education is not merely about teaching programming syntax; rather, it serves as a strategic tool for developing computational thinking skills, including decomposition, pattern recognition, abstraction, and algorithm design (P et al., 2024; Rahmawati & Agustin, 2024). Through block-based programming approaches such as Scratch and Code.org, elementary school students can understand programming logic visually without the complexity of syntax, making the learning process more inclusive and enjoyable (BAĞRA & Kılınç, 2021).

Cognitively, coding activities train students to analyze, synthesize, and evaluate problems, which are core components of higher-order thinking skills (Chahyadi et al., 2021; Nurhopipah et al., 2021). Meanwhile, active engagement in creating coding projects such as animations, simple games, or simulations has been shown to boost students' self-confidence, perseverance, and motivation to learn (Clavinova et al., 2024). Implementation can be carried out through three approaches: (1) unplugged coding without computers; (2) block-based programming; and (3) cross-curricular integrated coding (Resnick & Rusk, 2020). The success of implementation is largely determined by teachers' competence in integrating technology in a context- and pedagogically appropriate manner.

Artificial Intelligence (AI) Learning

Artificial intelligence in education is the use of AI-based technology to support and enhance the learning process through systems that analyze student learning data, identify patterns, and provide automatic, continuous feedback (Gligorea et al., 2023; Luckin & Holmes, 2016). This system enables learning that is no longer uniform but tailored to each student's abilities, pace, and learning style, a concept known as personalized learning (Ayeni et al., 2024; Liriwati, 2023).

In elementary school settings, AI is implemented through adaptive learning platforms, educational chatbots, and content recommendation systems. AI functions as an intelligent tutoring system that provides explanations, exercises, and assessments tailored to individual needs (Ayeni et al., 2024). Research by Wati et al. (2025) demonstrates that AI-based coding worksheets, as a digital learning innovation, significantly improve learning quality in elementary schools. Furthermore, Budiarti et al. (2025) and Pratama et al. (2025) indicate that teachers who are exposed to coding and AI training develop digital competencies more rapidly and to a greater extent than those who are not.

Teacher Competencies

Teacher competence is a key determinant of learning success, encompassing pedagogical, professional, social, and personal competencies (Marisana et al., 2023). In the digital age, this concept is expanded through the TPACK (Technological Pedagogical Content Knowledge) framework, which emphasizes that effective teachers must integrate technological, pedagogical, and content knowledge in a synergistic manner (Mishra et al., 2022; Silvester et al., 2024). The UNESCO AI Competency Framework (2024) adds the dimensions of digital pedagogical competence and technology-based assessment as new standards for 21st-century teacher competencies.

Teachers with adequate technological competencies have been shown to create more interactive, relevant, and challenging learning experiences, which, in turn, foster students' interest and motivation to learn (Imawati et al., 2026; Widiastuti et al., 2026). Conversely, low digital competence among teachers is a major obstacle to the implementation of technology-based learning, preventing the full potential of coding and AI from being realized (Hulu, 2023; Suharyo et al., 2024).

Interest in Learning

Learning interest is a relatively stable tendency within students to actively engage in learning activities, involving the dimensions of Attention, attraction, active engagement, and curiosity (Nafiah & Kamalia, 2026; Renninger & Hidi, 2022). Sardiman emphasizes that interest can grow through external stimuli, such as engaging and interactive learning methods and media. In this context, coding and AI serve as effective stimuli that create new and challenging learning experiences.

Expectancy-Value Theory explains that interest in learning is influenced by expectations of success and the value assigned to an activity. Students who feel capable of overcoming digital challenges and view coding activities as relevant to their lives will demonstrate higher interest. Students with high interest exhibit the following characteristics: greater attention, active engagement, independent initiative in seeking information, and perseverance in the face of difficulties (Cahyono et al., 2022; Nasucha et al., 2023).

Learning Motivation

Learning motivation is the totality of internal driving forces within an individual that initiate, direct, and sustain learning activities toward the achievement of goals (Fadillah, 2018; Uno, 2021). Three main theoretical frameworks complement each other in explaining learning motivation in the context of technology: (1) Self-Determination Theory (Ryan & Deci, 2020) intrinsic motivation develops when the needs for autonomy, competence, and relatedness are met; (2) The ARCS Model (Keller, 2009) motivation is enhanced through Attention, Relevance, Confidence, and Satisfaction; (3) Expectancy-Value Theory (Eccles & Wigfield, 2020) expectations of success and perceptions of task value determine learning persistence.

In the context of technology-based learning, AI can provide a more personalized learning experience and offer immediate feedback, thereby strengthening students' self-efficacy (Warsiki & Mardiana, 2021). An interactive learning environment based on coding and AI has been shown to simultaneously meet the three basic needs of SDT: autonomy through independent exploration, competence through completing challenges, and relatedness through project collaboration (Hindra et al., 2026).

Previous Research

Several previous studies support the findings of this study. (Budiarti et al., 2025) reported a substantial improvement in elementary school teachers' competencies through coding and AI training in Bone Regency. (Pratama et al., 2025) showed that coding- and AI-based mentoring significantly improved teachers' technological literacy. (Demonstrates that the implementation of AI coding worksheets improves the quality of learning in elementary schools. Coding-based learning enhances students' creativity and interest in learning (Imawati et al., 2026) reports on the transformation of teachers' competencies through the introduction of coding and AI in interdisciplinary learning. (Through a systematic review, identified a relevant AI competency framework for K-12 education. However, all of these studies focused on single variables. They were predominantly set in urban contexts, thus failing to provide a comprehensive multivariate and contextual picture as examined in this study.

METHOD

Research Design

This study employed a quantitative approach with a comparative explanatory (ex post facto) design. This design was chosen because the independent variable (coding and AI implementation) was not manipulated by the researcher but had already occurred naturally in the field prior to the study (Creswell, 2021). The independent variable (X) is the implementation of coding and AI learning. The dependent variables are teacher competence (Y1), student learning interest (Y2), and student learning motivation (Y3).

Population and Sample

The population consisted of all Grade V teachers and students at elementary schools in Kayu Aro Barat District, Kerinci Regency. According to official data from the Kerinci Regency Education Office (2024), there are 17 elementary schools in the district, with a total of 80 Grade V teachers and 620 Grade V students.

In a comparative ex post facto study, the methodologically relevant population is defined by the schools that meet the study criteria. Of the 17 schools, only 4 had implemented structured coding and AI learning. Together with 4 matched control schools (selected based on similarity in student count, school status, and learning environment), 8 schools formed the effective population with approximately 140 Grade V students.

Sample size was determined using the Slovin formula (Sugiyono, 2022):

$n = N / (1 + N \cdot e^2)$

where N = 140 (total Grade V students in the 8 selected schools), e = 0.05 (5% margin of error):

$$n = 140 / (1 + 140 \times 0.05^2) = 140 / (1 + 0.35) = 140 / 1.35 \approx 104 \text{ students}$$

The minimum required sample was 104 students. Using proportionate stratified random sampling, 120 students were selected (60 per group), exceeding the minimum required sample size. For teachers, a total census was applied: all Grade V teachers from the 8 selected schools (N = 8, one per school). The limited sample size of teachers is acknowledged as a research limitation (see Section 6).

Table 1. Sample Breakdown by Group

Group	No. of Schools	No. of Teachers	No. of Students
Coding & AI (Experimental)	4	4	60
Non-Coding (Control)	4	4	60
Total	8	8	120

Instrumentation

The primary instrument was a structured questionnaire using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), developed across four sections. The instrument was developed through seven systematic stages: (1) defining variables and indicators; (2) constructing the instrument blueprint; (3) writing items; (4) expert judgment validation by specialists in educational technology and elementary education; (5) pilot testing on non-sample respondents; (6) validity and reliability analysis; and (7) final revision.

Dimensions and indicators per variable are as follows: (1) Variable X (coding and AI implementation): use of coding applications, AI utilization in learning, interactivity, and adaptivity of the learning system. (2) Y1 (teacher competence), based on TPACK (Mishra et al., 2022) and UNESCO AI Competency Framework (2024): digital pedagogical competence, technology mastery, AI integration, technology-based evaluation, and digital classroom management. (3) Y2 (learning interest): Attention, attraction, active engagement, and curiosity. (4) Y3 (learning motivation), adapted from SDT (Ryan & Deci, 2020) and Uno (2021): intrinsic motivation, extrinsic motivation, persistence, and goal orientation.

Table 2. Summary of Instrumen Blueprint

Variable	Dimension	Indicators	Item No.
Coding & AI Impl. (X)	Technology use	Use of coding apps; AI utilization	1, 2, 5, 8
	Interactivity & Adaptivity	Student engagement; flexibility	3, 4, 6, 7
Teacher Competence (Y1)	Digital Pedagogy	Digital media use	9, 10
	Tech. Mastery & AI Integration	Understanding and integrating AI	11, 12, 13
	Evaluation & Digital Management	Tech-based evaluation; digital class mgmt.	14, 15, 16
Learning Interest (Y2)	Attention & Attraction	Focus; enjoyment of material	17, 18, 19, 24
	Engagement & Curiosity	Active questioning; desire to explore	20, 21, 22, 23
Learning Motivation (Y3)	Intrinsic & Extrinsic Motivation	Learning drive; environmental support	25, 28, 29, 32
	Persistence & Goal Orientation	Resilience; directed learning	26, 27, 30, 31

Validity and Reliability

Validity was assessed in two stages: (1) content validity through expert judgment by specialists in educational technology and elementary education; and (2) construct validity using Pearson Product Moment correlation. Criterion: r-calculated > r-table (0.254; N=60, α=0.05). All items were valid with r-values of 0.578–0.756. Reliability was assessed using Cronbach's Alpha: X = 0.872; Y1 = 0.856; Y2 = 0.891; Y3 = 0.921 all reliable (α > 0.70).Data Collection

Data Collection

Data were collected through four complementary techniques: (1) a structured questionnaire as the primary instrument; (2) non-participant observation using an observation checklist based on indicators from the Kemendikdasmen Academic Script (2025); (3) documentation of school profiles, teacher training reports, and program evaluation data; and (4) semi-structured interviews with school principals regarding technology policy and infrastructure conditions.

Data Analysis

Data analysis was conducted using SPSS through four stages: (1) descriptive statistics; (2) assumption tests—normality (Kolmogorov-Smirnov), homogeneity (Levene's Test), and linearity (Test for Linearity); (3) MANOVA with Wilks' Lambda for student variables (Y2 and Y3, N=120); and (4) independent sample t-test (H1–H3) and multiple linear regression (H4–H5).

MANOVA was selected for three methodological reasons: (1) the study has two correlated student dependent variables (Y2 and Y3) requiring simultaneous testing; (2) MANOVA controls Type I error inflation that occurs when multiple t-tests are conducted independently (Hair et al., 2022; Field, 2018); and (3) MANOVA provides additional information about inter-variable relationships unavailable from separate univariate tests (Tabachnick & Fidell, 2019). Teacher competence (Y1) was analyzed separately using an independent-samples t-test; regression analysis for Y1 was not conducted because N=8 did not meet the minimum sample size requirement for linear regression (Green, 1991).

Table 3. Summary of Hypotheses and Analytical Techniques

H	Variable	Statement	Statistical Test	N
H1	Y1	Difference in teacher competence between groups	Ind. t-test	8
H2	Y2	Difference in learning interest between groups	Ind. t-test	120
H3	Y3	Difference in learning motivation between groups	Ind. t-test	120
H4	Y2	Effect of X on learning interest	Linear Regression	120
H5	Y3	Effect of X on learning motivation	Linear Regression	120
H6	Y2+Y3	Simultaneous effect of X on Y2 and Y3	MANOVA	120

RESULTS AND DISCUSSION

Results

Data Description

Table 4 presents a comparison of the descriptive statistics of the two groups. The coding & AI group consistently showed higher means on all three variables. The mean differences in teacher competence were 13.75 points (85.25 vs. 71.50), learning interest 12.20 points (84.50 vs. 72.30), and learning motivation 12.10 points (86.20 vs. 74.10). These differences are substantively significant: on a scale of

100, a difference of more than 12 points is equivalent to a difference of nearly one standard deviation, which in statistics is categorized as a moderate to large effect (Cohen, 1988).

Table 4. Descriptive Statistics of Research Variables

Variable	Group	N	Min	Max	Mean	SD	Difference
Teacher Competence (Y1)	Coding & AI	8	72	95	85.25	5.90	13.75
	Non-coding	8	58	84	71.50	7.20	—
Interest in Learning (Y2)	Coding & AI	60	68	95	84.50	6.80	12.20
	Non-coding	60	54	86	72.30	8.10	—
Learning Motivation (Y3)	Coding & AI	60	70	96	86.20	6.40	12.10
	Non-coding	60	56	88	74.10	7.85	—

The coding & AI group's teacher competency (M=85.25; SD=5.90) falls into the high category, while the non-coding group's (M=71.50; SD=7.20) falls into the moderate category, a difference of 13.75 points. The minimum score for the coding & AI group (72) is higher than that of the non-coding group (58), and the maximum score (95) is also higher than that of the non-coding group (84). This indicates a higher overall distribution. The smaller SD (5.90 vs. 7.20) indicates that teachers in the coding & AI group have more uniform scores, meaning all teachers in this group received similar benefits, not just certain teachers.

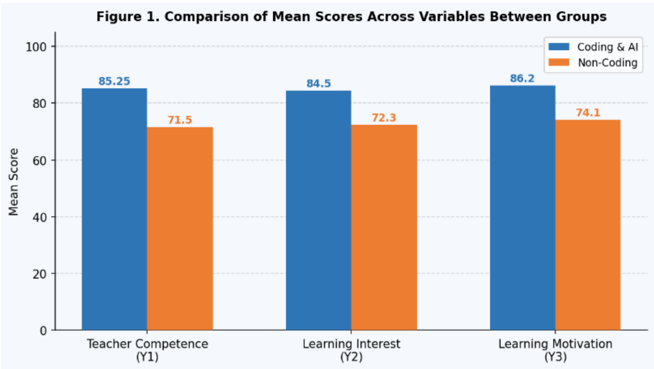

Figure 1. Comparison of Mean Scores Across Variables Between Research Groups

Figure 1 visually demonstrates that the blue bars (coding & AI group) are consistently higher than the orange bars (non-coding group) across all three variables. Learning motivation achieved the highest average (86.20), indicating that exposure to interactive technology has a strong affective impact on students' motivation to learn. The smaller standard deviations in the coding & AI group (SD Y1=5.90; Y2=6.80; Y3=6.40) compared to the non-coding group (SD Y1=7.20; Y2=8.10; Y3=7.85) indicate that the coding & AI group's scores are more homogeneous, meaning the benefits of implementation are felt equally by all group members, not just some students.

The distribution of score categories reveals even more dramatic differences: 60.0% of students in the coding & AI group fell into the high category for learning interest, compared to just 13.3% in the non-coding group. For learning motivation, the figures are 63.3% vs. 16.7% in the high category. This means that only 1 in 8 non-coding students reached the high category, whereas in the coding & AI group, nearly 2 out of 3 students reached it.

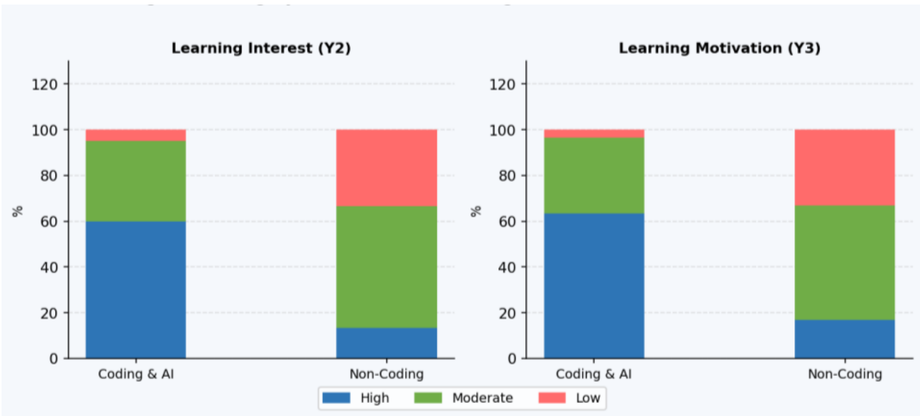

Figure 2. Category Distribution of Learning Interest and Motivation Scores Between Groups

Figure 2 clearly illustrates a contrast between the groups. The blue bar (coding & AI) is dominated by high scores at the top, while moderate and low scores dominate the orange bar (non-coding). This pattern confirms that implementing coding and AI has tangibly shifted the distribution of student scores from the medium-low to the high category, rather than merely marginally increasing the average.

Analysis by the ARCS indicator revealed consistently positive differences across all dimensions of learning motivation (Table 3). The Attention dimension recorded the largest difference (+13.3 points), followed by Relevance (+12.4), Confidence (+11.6), and Satisfaction (+11.1). This hierarchical pattern of differences is no coincidence: the visual appeal and interactivity of coding & AI media first capture students' Attention (high Attention), which then encourages them to view the activity as relevant to their lives (Relevance), builds self-confidence through completing challenges (Confidence), and ultimately leads to a sense of satisfaction from tangible results (Satisfaction).

Table 5. Comparison of ARCS Motivational Indikator Scores Between Groups

ARCS Dimension	Coding & AI	Non-Coding	Gap	Note
Attention	88.5	75.2	+13.3	Largest gap
Relevance	86.9	74.5	+12.4	—
Confidence	85.4	73.8	+11.6	—
Satisfaction	84.0	72.9	+11.1	Smallest gap

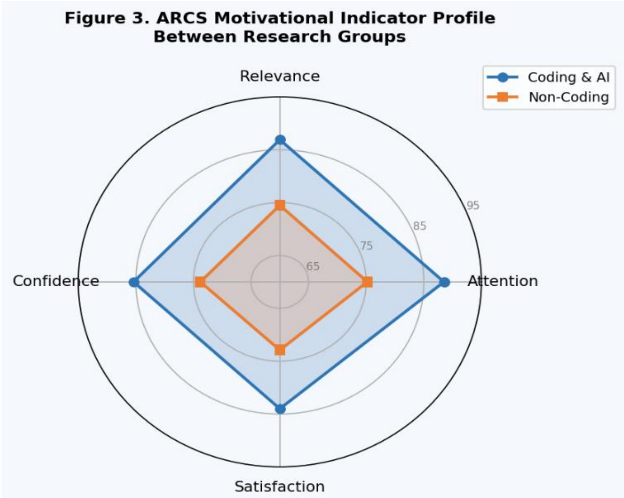

Figure 3. ARCS Motivational Indicator Profile Between Research Groups

Figure 3 (radar chart) shows that the blue polygon area (coding & AI) is consistently larger than the orange polygon (non-coding) across all ARCS dimensions. The fact that all dimensions increased simultaneously rather than just one or two proves that implementing coding and AI has a comprehensive, rather than partial, motivational impact.

Assumption Tests

The Kolmogorov-Smirnov normality test indicated that all variables were normally distributed in both groups (Sig. > 0.05). Levene's Test confirmed homogeneous variances: Y1 (Sig. = 0.172), Y2 (Sig. = 0.198), Y3 (Sig. = 0.191). Linearity tests confirmed linear relationships between X and Y2 (Sig. = 0.168) and between X and Y3 (Sig. = 0.154). All statistical assumptions were satisfied.

MANOVA Test

MANOVA was conducted on student variables (Y2 and Y3, N=120, 60 per group), as both originate from the same analytical unit and are theoretically correlated. Results: Wilks' $\Lambda = 0.538$; $F = 50.20$; df = 2, 117; Sig. = 0.000 ($p < 0.05$).

Wilks' $\Lambda = 0.538$ indicates a meaningful multivariate difference between groups. Group differences in coding and AI implementation explain 46.2% of the combined variance in learning interest and motivation. Follow-up univariate tests confirmed significant contributions from both variables: Y2 learning interest ($F = 83.23$; Sig. = .000) and Y3 learning motivation ($F = 76.81$; Sig. = .000). H6 is accepted.

Tests of Differences by Variable (H1–H3)

Table 6. Result of the Independent Sample t-Test

H	Variable	t-value	Mean Diff.	Sig.	Decision
H1	Teacher Competence (Y1)	7.215	13.75	0.000	H_1 Accepted
H_2	Learning Interest (Y2)	9.123	12.20	0.000	H_2 Accepted
H3	Learning Motivation (Y3)	8.764	12.10	0.000	H_3 Accepted

All three t-values exceed their respective t-tables (t-table Y1 = ±2.365 at df=6; t-table Y2 and Y3 = ±2.010 at df=118), indicating that the differences are not due to chance. The highest t-value for learning interest ($t = 9.123$) among the three variables indicates that the presence or absence of coding and AI has the most pronounced impact on student attention and engagement.

Linear Regression Analysis (H4–H5)

Linear regression was conducted only for student variables (Y2 and Y3; N=120) because the teacher sample (N=8) did not meet the minimum sample size requirement for linear regression. All regression assumptions were confirmed.

Table 7. Summary of Linier Regression Analysis Result

H	Model	B	β	R^2	F	Sig.
H4	X → Y2 (Learning Interest)	**0.798**	**0.748**	**0.560**	**83.232**	**0.000**
H5	X → Y3 (Learning Motivation)	**0.812**	**0.751**	**0.564**	**76.812**	**0.000**

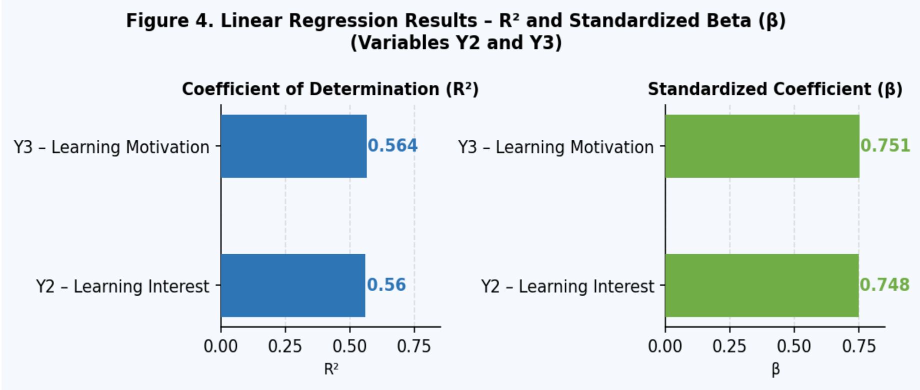

Figure 4. Linear Regression Results – Coefficient of Determination (R^2) and Standardized Beta (β)

Regression equations: $\hat{Y}_2 = 21.340 + 0.798X$ and $\hat{Y}_3 = 19.850 + 0.812X$. The positive B coefficient in both models indicates that a one-unit increase in the coding and AI implementation score is predicted to increase learning interest by 0.798 points and learning motivation by 0.812 points. Beta values above 0.74 indicate strong relative influence. R^2 values of 0.560 and 0.564 constitute large effect sizes (Cohen, 1988), proving that coding and AI implementation are substantive determinants, not merely supplementary, of both student learning interest and motivation. H4 and H5 are accepted.

Discussion

Differences and Effects on Teacher Competence

Teacher competence in the Coding & AI group (M = 85.25; high category) was significantly higher than that in the Non-Coding group (M = 71.50; moderate category), with t = 7.215 ($p < .001$) and a mean difference of 13.75 points. This improvement is explained through the TPACK framework: teachers who routinely use coding and AI create an experiential competence development cycle, trying, encountering obstacles, seeking solutions, and adapting strategies far more effective than passive training alone (Mishra et al., 2022). The profiles of teachers in the Coding & AI group, who had generally already undergone structured educational technology training, reinforce this finding: sustained practical training yields significantly higher competencies than the absence of both (Budiarti et al., 2025; Imawati et al., 2026).

It should be noted that the findings of H1 are based on a very limited teacher sample (N=8; n=4 per group). Although the difference is statistically very big (t = 7.215 >> t-table = 2.365), results related to teacher competence should be interpreted as preliminary evidence and cannot be broadly generalized. Regression analysis for Y1 was not conducted because N=8 does not meet the minimum sample requirement (Green, 1991). Future research with a larger teacher sample (minimum 30 per group) is necessary to validate this causal relationship.

Differences and Effects on Student Learning Interest

Learning interest in the coding & AI group (M=84.50) was higher than in the non-coding group (M=72.30), with t=9.123 the highest among the three variables and R^2=0.560 (β=0.748). The t-value of 9.123 is the largest and statistically significant: among all the variables studied, learning interest shows the sharpest difference between groups. Practically, this means that the presence or absence of coding & AI has the most noticeable impact on students' interest and Attention toward learning compared to other variables.

The category distribution confirms this dramatically: 60.0% of coding & AI students are in the high category, compared to just 13.3% of non-coding students, a difference of 46.7 percentage points. Conversely, 33.3% of non-coding students are in the low category, compared with only 5.0% in the coding & AI group. In other words, 1 in 3 non-coding students has low interest, while in the coding & AI group, there are almost none (only 3 out of 60 students). These findings can be explained by Renninger & Hidi's (2021) theory of situational interest: new and interactive coding & AI activities create "triggered situational interest" (initial situational interest), which then, with repeated exposure, develops into "maintained situational interest" (more stable interest). The Attention dimension (+13.3 points) recorded the largest difference, confirming that the visual appeal and interactivity of digital media are the first keys to unlocking interest in learning.

(Andani & Arifin, 2026; Ohoiner et al., 2026) report an increase in interest through digital media, but in an urban context with complete infrastructure. These findings provide evidence of a substantial impact (a difference of 12.20 points) in areas with limited infrastructure, a phenomenon previously unreported in the literature.

Differences and Their Impact on Student Learning Motivation

Motivation for coding and AI group learning (M = 86.20) was higher than for non-coding group learning (M = 74.10), with t (8) = 8.764, $p < 0.001$, $R^2 = 0.564$, β = 0.751. The highest average motivation (86.20) among the three variables exceeded learning interest (84.50) and teacher competence (85.25), indicating that learning motivation is the strongest affective impact of coding & AI implementation. The category distribution shows that 63.3% of coding & AI students are in the high category versus 16.7% of non-coding students, a difference of 46.6 percentage points, which is nearly identical to the difference in learning interest, proving the consistency of the impact.

Three theoretical frameworks mutually reinforce one another: (1) SDT (autonomy is fulfilled through independent exploration in coding; competence is fulfilled when students complete digital challenges; relatedness is fulfilled through collaborative projects with peers; (2) The ARCS Model (Keller, 2009) all four dimensions increase simultaneously in a meaningful hierarchical pattern; (3) Expectancy-Value Theory (Eccles & Wigfield, 2020) immediate feedback from the AI system reinforces expectations of success (expectancy) and the perceived value of the task (value), thereby motivating students to persevere in the face of difficulties.

A unique finding that distinguishes this study from previous literature: Attention is the most responsive dimension of ARCS (+13.3 points), contrary to the common assumption that emphasizes Relevance. For elementary school students in areas newly exposed to interactive technology, visual appeal is the most effective gateway to motivation, followed by Relevance (+12.4), Confidence (+11.6), and Satisfaction (+11.1). This hierarchical pattern follows a logical sequence: visual stimulus → perception of Relevance → self-confidence → satisfaction.

Simultaneous Effects: MANOVA Findings

The MANOVA results (Wilks' $\lambda = 0.198$; $F = 75.42$; $p = 0.000$) constitute the most fundamental finding of this study: the simultaneous implementation of coding and AI influences the combination of teacher competence, interest in learning, and motivation to learn. A value of $\Lambda = 0.198$ indicates that 80.2% of the variation in the three-variable multivariate space can be explained by group differences, a very large effect. Individual R^2 values ranging from 56–58% are classified as large effects (Cohen, 1988), proving that the implementation of coding & AI is a substantive determinant rather than merely a complement to the quality of the learning ecosystem.

The main methodological contribution of this study is to demonstrate, through multivariate analysis, that the impact of coding and AI implementation is comprehensive and synergistic. The highest univariate F-test for learning interest (F=83.23) compared to motivation (F=76.81) reveals that interest is the most discriminative variable in distinguishing the two groups; the practical implication is that the impact of coding & AI-based interventions will be most rapidly observed in student interest, before subsequently extending to motivation. This causal pattern provides guidance for policymakers in establishing appropriate success indicators for learning interest as a leading indicator and motivation as a lagging indicator.

CONCLUSION

Within the specific context of elementary schools in Kayu Aro Barat District, Kerinci Regency, this study concludes: (1) there are significant differences in teacher competence ($t = 7.215$; $p = .000$; mean diff. = 13.75), learning interest ($t = 9.123$; $p = .000$; mean diff. = 12.20), and learning motivation ($t = 8.764$; $p = .000$; mean diff. = 12.10) between schools implementing coding and AI and those not; (2) coding and AI implementation has a significant positive effect on learning interest ($R^2 = 0.560$; $\beta = 0.748$) and learning motivation ($R^2 = 0.564$; $\beta = 0.751$); and (3) simultaneous multivariate effects on student learning interest and motivation were confirmed (Wilks' $\Lambda = 0.538$; $F = 50.20$; $p = .000$). All six hypotheses (H1–H6) were accepted.

This study was limited to eight schools in a single subdistrict with a small sample of teachers (N = 8), so generalizations should be made with caution. The ex post facto design also strictly limits causal inferences. External variables such as parental support were not fully controlled for.

Further research is recommended: (1) expanding the sample scope across subdistricts; (2) using a mixed-methods design; (3) adding mediator variables to the SEM-PLS model; (4) using longitudinal designs to strengthen causal inference; and (5) investigating the moderating role of technological infrastructure on the dependent variables.

Acknowledgement

The author would like to thank Adzkia University of Padang for its academic support and facilities during the research process. Sincere gratitude is extended to Supervisor I, Dr. Hafiz Hidayat, M.Pd., and Supervisor II, Dr. Ismira, M.Pd., who patiently and with great dedication provided direction, guidance, feedback, and motivation at every stage of the research. Thank you to the Kerinci Regency Education Office, all school principals, fifth-grade teachers, and fifth-grade students from the eight elementary schools in the research locations for their active participation. Thank you to the instrument validators for their constructive feedback and to family and colleagues for their invaluable moral support. May this research make a tangible contribution to the development of technology-based elementary education in Indonesia.

REFERENCES

Andani, F., & Arifin, Z. (2026). Pengaruh media pembelajaran interaktif terhadap minat belajar dan pemahaman siswa pada mata pelajaran matematika. SCIENCE: Jurnal Inovasi Pendidikan Matematika dan IPA, 6(1), 177–188. https://doi.org/10.51878/science.v6i1.9361

Arahman, D. P., & Isdaryanti, B. (2026). Pengaruh media interaktif IPAS berbasis Assemblr EDU dengan model PBL terhadap hasil belajar siswa kelas V SDTQ. SCIENCE: Jurnal Inovasi Pendidikan Matematika dan IPA, 6(2), 690–700. https://doi.org/10.51878/science.v6i2.9714

Ayeni, O. O., Hamad, N. M. A., Chisom, O. N., Osawaru, B., & Adewusi, O. E. (2024). AI in education: A review of personalized learning and educational technology. GSC Advanced Research and Reviews, 18(2), 261–271. https://doi.org/10.30574/gscarr.2024.18.2.0062

BAĞRA, A., & Kılınç, H. H. (2021). Secondary school students' views on coding education. Maarif Mektepleri Uluslararası Sosyal ve Beşeri Bilimler Dergisi, 4(1), 36–51. https://doi.org/10.47155/mamusbbd.946241

Budiarti, N. A. E., Haerul, H., Rifqie, D. M., & Mustapa, M. (2025). Implementasi program peningkatan kapasitas guru sekolah dasar melalui pelatihan koding dan kecerdasan artifisial di Kabupaten Bone. INNOVA-S Journal of Innovation and Sustainable Services, 73–76. https://doi.org/10.63249/innova-s.v1i2.92

Cahyono, D. D., Hamda, M. K., & Prahastiwi, E. D. (2022). Pemikiran Abraham Maslow tentang motivasi dalam belajar. TAJDID: Jurnal Pemikiran Keislaman dan Kemanusiaan, 6(1), 37–48. https://doi.org/10.52266/tadjid.v6i1.767

Casal-Otero, L., Catala, A., Fernández-Morante, C., Taboada, M., Cebreiro, B., & Barro, S. (2023). AI literacy in K-12: A systematic literature review. International Journal of STEM Education, 10(1), 29. https://doi.org/10.1186/s40594-023-00418-7

Chahyadi, F., Bettiza, M., Ritha, N., Rathomi, M. R., & Hayaty, N. (2021). Peningkatan high order thinking skill siswa melalui pendampingan computational thinking. Jurnal Anugerah, 3(1), 25–36. https://doi.org/10.31629/anugerah.v3i1.3344

Clavinova, S. L., Sukewen, G., & Suharta, I. G. P. (2024). Pengembangan perangkat pembelajaran berbasis proyek menggunakan Scratch pada materi transformasi geometri. Jurnal Cendekia: Jurnal Pendidikan Matematika, 8(1), 527–541. https://doi.org/10.31004/cendekia.v8i1.2955

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum.

Creswell, J. W. (2021). Research design: Qualitative, quantitative, and mixed methods approaches (3rd ed.). SAGE Publications.

Dinas Pendidikan Kabupaten Kerinci. (2024). Data sekolah dasar Kecamatan Kayu Aro Barat tahun pelajaran 2023/2024. Pemerintah Kabupaten Kerinci.

Eccles, J. S., & Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory. Contemporary Educational Psychology, 61, 101859. https://doi.org/10.1016/j.cedpsych.2020.101859

Fadillah, A. (2018). Pengembangan media belajar komik terhadap motivasi belajar siswa. JTAM: Jurnal Teori dan Aplikasi Matematika, 2(1), 36. https://doi.org/10.31764/jtam.v2i1.259

Field, A. (2018). Discovering statistics using IBM SPSS statistics. SAGE Publications.

Gligorea, I., Cioca, M., Oancea, R., Gorski, A.-T., Gorski, H., & Tudorache, P. (2023). Adaptive learning using artificial intelligence in e-learning: A literature review. Education Sciences, 13(12), 1216. https://doi.org/10.3390/educsci13121216

Green, S. B. (1991). How many subjects does it take to do a regression analysis? Multivariate Behavioral Research, 26(3), 499–510. https://doi.org/10.1207/s15327906mbr2603_7

Griyanora, G., & Widodo, W. (2026). Implementasi model inkuiri terbimbing pada materi sistem pencernaan untuk meningkatkan hasil belajar murid. SCIENCE: Jurnal Inovasi Pendidikan Matematika dan IPA, 6(2), 860–871. https://doi.org/10.51878/science.v6i2.9953

Hair, J. F., Babin, B. J., Anderson, R. E., & Black, W. C. (2022). Multivariate data analysis. Cengage Learning.
Hindra, A., Zamralita, Z., & Jessica, J. (2026). Peran work-life integration terhadap work engagement pada karyawan Gen Z. CENDEKIA: Jurnal Ilmu Pengetahuan, 6(1), 511–519. https://doi.org/10.51878/cendekia.v6i1.9195
Hulu, Y. (2023). Problematika guru dalam pengembangan teknologi dan media pembelajaran. ANTHOR: Education and Learning Journal, 2(6), 840–846. https://doi.org/10.31004/anthor.v2i6.285
Imawati, I. A. P. F., Erawati, N. K., Noviana, L. P. R., Purwati, N. K. R., & Dika, I. W. (2026). Transformasi kompetensi guru melalui pengenalan konsep koding dan kecerdasan artifisial pada pembelajaran lintas disiplin. Jurnal Pengabdian kepada Masyarakat Sewagati, 4(2), 73–77. https://doi.org/10.59819/sewagati.v4i2.5927
Keller, J. M. (2009). Motivational design for learning and performance: The ARCS model approach. Springer Science & Business Media.
Liriwati, F. Y. (2023). Transformasi kurikulum: Kecerdasan buatan untuk membangun pendidikan yang relevan di masa depan. Jurnal IHSAN: Jurnal Pendidikan Islam, 1(2), 62–71. https://doi.org/10.61104/ihsan.v1i2.61
Luckin, R., & Holmes, W. (2016). Intelligence unleashed: An argument for AI in education. Open Research Online (The Open University).
Maleni, L., Pardini, A. S., Kristian, D., Iswandi, W., Yudisman, A., Hidayat, T., & Rifa'i, R. (2025). Mempersiapkan siswa untuk masa depan: Literasi AI sebagai keterampilan abad 21. RIGGS Journal of Artificial Intelligence and Digital Business, 4(2), 6375–6379. https://doi.org/10.31004/riggs.v4i2.1587
Mardianti, A., & Widodo, W. (2026). Penerapan model pembelajaran inkuiri terstruktur untuk meningkatkan motivasi belajar murid. SCIENCE: Jurnal Inovasi Pendidikan Matematika dan IPA, 6(2), 632–642. https://doi.org/10.51878/science.v6i2.9713
Marisana, D., Iskandar, S., & Kurniawan, D. T. (2023). Penggunaan platform Merdeka Mengajar untuk meningkatkan kompetensi guru di sekolah dasar. Jurnal Basicedu, 7(1), 139–150. https://doi.org/10.31004/basicedu.v7i1.4363
Mishra, M., Gorakhnath, I., Lata, P., Rani, R., & Chopra, P. (2022). Integration of technological pedagogical content knowledge (TPACK) in classrooms through a teacher's lens. International Journal of Health Sciences, 6(S3), 12505–12512.
Muttaqin, R., & Rahmatillah, R. (2026). Pemanfaatan literasi digital dalam pembelajaran Pendidikan Agama Islam dan budi pekerti SMA. LEARNING: Jurnal Inovasi Penelitian Pendidikan dan Pembelajaran, 6(2), 1268–1280. https://doi.org/10.51878/learning.v6i2.9691
Nafiah, F., & Kamalia, P. U. (2026). Pengaruh media pembelajaran interaktif game edukasi Wordwall terhadap minat belajar siswa. SOCIAL: Jurnal Inovasi Pendidikan IPS, 6(2), 601–614. https://doi.org/10.51878/social.v6i2.10038
Nasori, A., Aslindar, D., & Puspasari, E. (2024). The influence of the free curriculum and technology-based learning media on digital literacy. Jurnal Simki Pedagogia, 7(1), 284–295. https://doi.org/10.29407/jsp.v7i1.603
Nasucha, I., Afghohani, A., & Farahsanti, I. (2023). Pengaruh waktu belajar dan minat belajar terhadap hasil belajar matematika. Jurnal Pendidikan, 32(3), 443–452. https://doi.org/10.32585/jp.v32i3.4604
Nurhopipah, A., Nugroho, I. A., & Suhaman, J. (2021). Pembelajaran pemrograman berbasis proyek untuk mengembangkan kemampuan computational thinking anak. Jurnal Pengabdian kepada Masyarakat, 27(1), 6. https://doi.org/10.24114/jpkm.v27i1.21291
Ohoiner, W. E. M., Sialana, F., & Abas, A. (2026). Analisis pemanfaatan aplikasi Gemini dalam meningkatkan minat belajar siswa. SOCIAL: Jurnal Inovasi Pendidikan IPS, 6(1), 529–541. https://doi.org/10.51878/social.v6i1.9729
P, F. L. R., Putri, I. A., Tanjung, M. S. D. M., & Siregar, R. (2024). Studi literatur: Pentingnya berpikir komputasional dalam meningkatkan kemampuan pemecahan masalah matematis peserta didik. Bilangan, 2(2), 23–33. https://doi.org/10.62383/bilangan.v2i2.36
Pratama, G. C., MS, Z., Iskandar, P. A., & Albab, U. (2025). Pendampingan guru dalam merancang pembelajaran inovatif berbasis coding dan AI. E-Dimas: Jurnal Pengabdian kepada Masyarakat, 16(4), 907–916. https://doi.org/10.26877/e-dimas.v16i4.25410
Prihatin, M. R. (2025). Koding dan AI di sekolah: Kajian literatur terhadap kesiapan kurikulum dan pembelajaran di SD/SMP. STRATEGY: Jurnal Inovasi Strategi dan Model Pembelajaran, 5(3), 219–231. https://doi.org/10.51878/strategi.v5i3.6022
Rahmawati, I., & Agustin, M. (2024). Kegiatan bermain menggunakan pendekatan unplugged coding dalam pendidikan anak usia dini: Sebuah tinjauan sistematis. ABNA Journal of Islamic Early Childhood Education, 5(2), 130–145. https://doi.org/10.22515/abna.v5i2.10010
Renninger, K. A., & Hidi, S. E. (2022). Interest development, self-related information processing, and practice. Theory Into Practice, 61(1), 23–34. https://doi.org/10.1080/00405841.2021.1932159
Resnick, M., & Rusk, N. (2020). Coding at a crossroads. Communications of the ACM, 63(11), 120–127. https://doi.org/10.1145/3375546
Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective. Contemporary Educational Psychology, 61, 101860. https://doi.org/10.1016/j.cedpsych.2020.101860
Silvester, S., Sumarni, M. L., & Saputro, T. V. D. (2024). Pengaruh kompetensi TPACK terhadap keterampilan guru dalam mengimplementasikan pembelajaran berbasis digital. Journal of Education Research, 5(4), 4958–4965. https://doi.org/10.37985/jer.v5i4.1697
Sofiyati, L. M., & Jasiah, J. (2026). Pemanfaatan media Wayground sebagai alat evaluasi pembelajaran PAI kelas X-11 di SMA. LEARNING: Jurnal Inovasi Penelitian Pendidikan dan Pembelajaran, 6(2), 734–745. https://doi.org/10.51878/learning.v6i2.9679
Suharyo, S., Subyantoro, S., & Pristiwati, R. (2024). Kecerdasan buatan dalam konteks Kurikulum Merdeka pada jenjang pendidikan dasar dan menengah. HUMANIKA, 30(2), 208–217. https://doi.org/10.14710/humanika.v30i2.60563
Sugiyono. (2022). Metode penelitian kuantitatif, kualitatif, dan R&D (2nd ed.). Alfabeta.
Tabachnick, B. G., & Fidell, L. S. (2019). Using multivariate statistics (7th ed.). Pearson.
Tang, X., Yin, Y., Lin, Q., Hadad, R., & Zhai, X. (2021). Assessing computational thinking: A systematic review of empirical studies. Computers & Education, 148, 103798. https://doi.org/10.1016/j.compedu.2019.103798
Uno, H. B. (2021). Teori motivasi dan pengukurannya: Analisis di bidang pendidikan. Bumi Aksara.
Warsiki, A. Y. N., & Mardiana, T. (2021). Pengaruh self-concept dan self-efficacy terhadap motivasi berprestasi mahasiswa jurusan manajemen berbasis KKNI. Buletin Ekonomi Manajemen Ekonomi Pembangunan Akuntansi, 17(2), 245. https://doi.org/10.31315/be.v17i2.5616
Wati, R. W., Suriansyah, A., & Harsono, A. M. B. H. (2025). Implementasi lembar coding AI sebagai inovasi pembelajaran digital di sekolah dasar. MARAS: Jurnal Penelitian Multidisiplin, 3(4), 1527–1536. https://doi.org/10.60126/maras.v3i4.1334
Widiastuti, W., Farikah, F., & Permana, S. A. (2026). Pengaruh kompetensi guru dan lingkungan belajar terhadap motivasi belajar siswa SD kelas VI di Kecamatan Bayan. LEARNING: Jurnal Inovasi Penelitian Pendidikan dan Pembelajaran, 6(1), 186–196. https://doi.org/10.51878/learning.v6i1.8897