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GENFABET
Generasi Pendidikan Dasar

GENFABET | e–ISSN 3063-7015 | Vol. 2 No. 2. (2026)

Reseacrh Article

The Effect of Metacognitive-Based Deep Learning Models in Mathematics Learning on the Academic Resilience of Elementary School Students

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Abstract: Mathematics learning at the elementary level is often associated with anxiety and low academic resilience, which may hinder students' persistence and performance. Strengthening resilience through innovative instructional models is therefore essential. This study aims to examine the effect of a Metacognitive-Based Deep Learning model on the academic resilience of elementary school students in mathematics. A quantitative true experimental design with a posttest-only control group was employed. The sample consisted of 120 fourth- and fifth-grade students divided equally into experimental and control groups. Data were collected using a 20-item mathematical resilience questionnaire measuring value, struggle, growth, and perseverance. Confirmatory Factor Analysis using PLS-SEM confirmed the validity and reliability of the instrument. Data were analyzed through an independent samples t-test, Cohen's d effect size, and two-way ANOVA. The results revealed a highly significant difference between groups ($p < .001$), with a mean difference of 24.233 points and a very large effect size ($d = 3.46$). The findings indicate that the intervention consistently improved students' academic resilience across grade levels without significant interaction effects. This study contributes theoretically by reinforcing the role of deep learning integrated with metacognitive strategies in developing non-cognitive competencies in elementary education. Practically, it offers an evidence-based instructional alternative to enhance students' resilience and reduce mathematics anxiety.

Keywords: academic resilience, deep learning, elementary education, mathematics learning, metacognition

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How to Cite: Bayu, M., & Dewi, S. M. (2026). The Effect of Metacognitive-Based Deep Learning Models in Mathematics Learning on the Academic Resilience of Elementary School Students. *GENFABET: Generasi Pendidikan Dasar*, 2(2), 14-28. https://doi.org/10.70152/genfabet.v2i2.342

Article submitted 2026-02-23. **Revision uploaded** 2026-02-25. **Final acceptance** 2026-02-26.

INTRODUCTION

Education is a dynamic process that integrates cognitive and non-cognitive aspects to prepare learners for the increasingly complex challenges of the world (Sultanova, 2025). This process is not only oriented toward mastery of subject matter but also focuses on character development, self-regulation, and resilience in facing academic pressure. The elementary school period represents a fundamental phase in shaping academic character and thinking skills, which determine the continuity of students' learning achievement (Akbaba, 2020). A strong foundation at this stage influences students' readiness to meet the demands of learning at higher levels.

Mathematics learning at the elementary level often generates anxiety due to its abstract nature and the high demand for reflection and self-control (Y. Wang et al., 2024). Such situations can reduce students' confidence and perseverance in completing mathematical tasks. Academic resilience becomes a key factor that enables students to overcome learning obstacles and maintain motivation when facing mathematical difficulties (Yang & Wang, 2022). Strengthening resilience from the elementary stage is essential to help students survive and thrive in challenging learning environments.

This topic is important because mathematics is often associated with negative attitudes and anxiety, as reported by the Organization for Economic Co-operation and Development, as well as high dropout rates, thereby highlighting the role of mathematical resilience in enhancing students' self-efficacy and learning persistence (Xenofontos & Mouroutsou, 2023). Variations in learning styles among elementary students are significantly related to mathematical resilience, particularly when facing problem-solving challenges (Sitorus et al., 2025). Mathematical resilience directly contributes to improving problem-solving skills, including significant gains in fraction problem-solving (Fitriani et al., 2023). Appropriate learning strategies can strengthen academic endurance while enhancing students' cognitive performance in mathematics.

Contextual and constructive learning approaches have been shown to reinforce both resilience and numeracy literacy compared to conventional instruction (Levi, 2024). Learning environments that provide space for exploration and reflection encourage students to confront academic difficulties more confidently. Recent research positions the integration of metacognitive strategies within deep learning models as an approach that promotes deeper student reflection and control over thinking processes (Rui et al., 2025). This integration is relevant for fostering awareness of learning strategies while enhancing resilience in the mathematical problem-solving process.

Metacognition in mathematics learning has been proven to improve conceptual understanding and help regulate students' emotions, which are closely linked to resilience in overcoming learning challenges (Panaoura, 2025). The implementation of metacognitive strategies through quasi-experimental designs demonstrates a positive effect on higher-order thinking skills in mathematics (Mohamed et al., 2025). Metacognitive interventions are also identified as a key factor in building academic resilience through increased monitoring and learning control (Anthonysamy, 2023). Strengthening self-regulation through deep learning models integrated with metacognition is expected to enhance reflection, control over learning processes, and creative solutions to contextual mathematical challenges.

However, although previous studies have examined deep learning models in mathematics education and others have investigated metacognitive strategies or academic resilience separately, there remains limited empirical research that explicitly integrates metacognitive-based deep learning models and examines their direct causal impact on academic resilience at the elementary school level. Most prior studies focus primarily on cognitive outcomes such as achievement or higher-order thinking skills, while the non-cognitive dimension—particularly academic resilience—has not been systematically analyzed as a primary dependent variable within an experimental framework. Furthermore, few studies have tested this integration using a controlled experimental design that allows for stronger causal inference.

Therefore, this study addresses this research gap by experimentally investigating the effect of a metacognitive-based deep learning model in mathematics instruction on elementary students' academic resilience. The novelty of this research lies in three main aspects: (1) the explicit integration of deep learning principles with structured metacognitive regulation strategies within a unified instructional model; (2) the positioning of academic resilience as the primary outcome variable rather than as a secondary or correlational construct; and (3) the use of an experimental design to provide empirical evidence of causal relationships between instructional intervention and students' resilience development.

Conceptually, this study proposes that the metacognitive-based deep learning model enhances students' reflective thinking, self-monitoring, and strategic regulation during mathematical problem-solving activities. These processes are expected to strengthen students' perceived competence, emotional regulation, and persistence, which in turn contribute to higher levels of academic resilience. Thus, the hypothesized direction of influence is that the instructional model (independent variable) positively affects metacognitive regulation processes, which subsequently foster improved academic resilience (dependent variable).

The positive relationship between mathematical resilience and mathematical ability suggests that increasing academic endurance leads to better learning performance. The development of learning models that combine deep learning and metacognitive strategies is therefore increasingly important in the context of elementary education. Integrating these two approaches offers opportunities to create learning experiences that are not only focused on cognitive outcomes but also on students' psychological resilience.

Accordingly, this study aims to analyze the effect of a metacognitive-based deep learning model in mathematics learning on the academic resilience of elementary school students, while providing a clear conceptual framework and empirical evidence to strengthen the theoretical and practical foundations of mathematics education.

THEORETICAL FRAMEWORK

The concept of deep learning in education is understood as an instructional approach that promotes meaningful, integrative, and reflective knowledge construction, enabling students to connect new information with prior understanding (Weng et al., 2023). Deep learning contrasts with surface learning by emphasizing conceptual understanding, problem-solving transfer, and active cognitive engagement. In mathematics education, deep learning environments encourage students to analyze patterns, justify reasoning, and construct conceptual meaning rather than merely apply procedural rules.

The integration of metacognitive strategies within mathematics instruction further strengthens students' ability to plan, monitor, and evaluate their own thinking processes (G. Wang et al., 2022). Metacognition, as conceptualized by Flavell, consists of metacognitive knowledge and metacognitive regulation, both of which play critical roles in mathematical problem-solving. In complex mathematical contexts, metacognitive regulation enables students to identify errors, revise strategies, and persist in the face of difficulty (Scheibe et al., 2023). Thus, metacognition functions as a self-regulatory mechanism that supports both cognitive performance and emotional control.

Recent empirical studies indicate that deep learning models significantly enhance higher-order thinking skills and conceptual mastery in mathematics (Rui et al., 2025), while metacognitive interventions improve students' strategic regulation and problem-solving accuracy (Mohamed et al., 2025). However, these studies predominantly measure cognitive outcomes such as achievement, reasoning ability, or critical thinking, and rarely position academic resilience as the primary dependent variable. Furthermore, the combined effect of deep learning and structured metacognitive regulation on elementary students' academic resilience remains underexplored in experimental research.

Academic resilience is defined as students' capacity to persist, adapt, and recover when encountering academic challenges (Shen et al., 2024). In mathematics learning, resilience is reflected in students' willingness to confront difficult problems, regulate frustration, and sustain effort despite repeated errors. The Survey on Social and Emotional Skills developed by the Organisation for Economic Co-operation and Development provides a validated framework for assessing emotional regulation and perseverance among 10-year-old students (F. Wang et al., 2025). Mathematical resilience has been found to positively correlate with problem-solving competence, self-efficacy, and learning persistence (Asare et al., 2025). These findings suggest that resilience is not merely an affective construct but is closely intertwined with cognitive engagement in mathematics.

Despite the growing body of literature on mathematical resilience, most prior studies examine it through correlational designs or as a mediating variable between anxiety and achievement. There is limited experimental evidence investigating how specific instructional models directly influence academic resilience as an outcome variable, particularly at the elementary school level. Moreover, few studies explicitly integrate deep learning principles and metacognitive regulation within a unified instructional framework aimed at strengthening resilience.

Based on self-regulated learning theory and constructivist learning principles, this study proposes that a metacognitive-based deep learning model enhances academic resilience through three primary mechanisms: (1) strengthening cognitive reflection during mathematical reasoning; (2) improving self-monitoring and strategic regulation during problem-solving; and (3) fostering emotional control and persistence when facing academic setbacks. Deep learning activities create cognitively demanding tasks that require meaningful engagement, while metacognitive scaffolding guides students in regulating their responses to these challenges.

Conceptually, the framework of this study positions the metacognitive-based deep learning model as the independent variable and academic resilience as the dependent variable. The model assumes a direct positive causal relationship, where structured metacognitive regulation embedded within deep learning activities leads to improved resilience indicators, including perseverance, adaptive coping, growth orientation, and confidence in mathematical tasks.

The hypothesized relationship can therefore be formulated as follows:

- H_1: Students who receive mathematics instruction through a metacognitive-based deep learning model will demonstrate significantly higher academic resilience than students who receive conventional instruction.

This conceptual model provides the theoretical foundation for employing a true-experimental design to test causal effects. The framework also guides the operationalization of research instruments, ensuring that resilience indicators (e.g., persistence, value of struggle, growth mindset orientation, and adaptive coping) are directly aligned with the theoretical constructs underlying metacognitive regulation and deep learning principles.

In summary, the synthesis of constructivist learning theory, self-regulated learning theory, and resilience theory establishes a coherent explanatory pathway linking instructional intervention to psychological outcomes in mathematics education. The theoretical contribution of this study lies in bridging cognitive-oriented instructional models (deep learning and metacognition) with a non-cognitive outcome variable (academic resilience) within an experimental framework at the elementary level. This integration strengthens the conceptual clarity and empirical relevance of the study in addressing the problem of low academic resilience in mathematics learning through a systematic and evidence-based approach.

METHODS

Research Design

This study employed a quantitative approach using an experimental design with a posttest-only control group structure. The experimental class received an intervention through a metacognitive-based deep learning model, while the control class participated in conventional mathematics instruction. The design aimed to examine the causal effect of the instructional model on students' academic resilience (Creswell & Creswell, 2018)

Table 1. Posttest-Only Control Group Design

Group	Treatment	Post-test
Experiment	X	O_1
Control	-	O_2

Table 1 illustrates the posttest-only control group design involving two groups: the experimental class and the control class. The experimental class received the treatment (X), while the control class did not receive the intervention. Outcome measurement was conducted once after the intervention through a post-test, recorded as O_1 for the experimental class and O_2 for the control class. The comparison between O_1 and O_2 was used to determine the effect of the treatment on academic resilience without administering a pre-test.

Although this study was designed as a true experiment, the assignment of students was conducted at the class level rather than the individual level due to administrative constraints. Two intact classes at each grade level were randomly assigned to either the experimental or control condition using a simple lottery method. Therefore, the study can be categorized as a cluster-randomized experimental design.

To minimize selection bias and ensure initial group equivalence, the researchers compared students' prior mathematics achievement scores from the previous semester using an independent samples t-test before the intervention. The results indicated no statistically significant differences between the groups ($p > .05$), suggesting comparable baseline academic ability. Additionally, demographic characteristics such as grade level distribution and gender proportion were balanced across groups. These procedures strengthen the internal validity of the causal inference.

Sample

The study was conducted at the elementary school level, involving fourth- and fifth-grade students. The participants were divided into two groups: the experimental class and the control class, each consisting of 60 students. Each group included 30 fourth-grade students and 30 fifth-grade students. The total sample comprised 120 students.

The use of intact classrooms was intended to maintain ecological validity and avoid disruption of the school's instructional structure. However, because randomization occurred at the class level, there remains a potential risk of cluster effects. To address this possibility, grade level (fourth and fifth grade) was included as a factor in the two-way ANOVA analysis to control for potential interaction effects between treatment and grade level.

Instructional Procedure

The intervention was conducted over eight instructional sessions (four weeks), with two mathematics lessons per week, each lasting 80 minutes. Both groups were taught the same mathematical topics aligned with the school curriculum.

Experimental Group: Metacognitive-Based Deep Learning Model
The instructional phases in the experimental group followed five structured stages:

1. Problem Orientation – Students were presented with contextual and cognitively demanding mathematical problems.
2. Deep Exploration – Students worked collaboratively to explore multiple solution strategies and construct conceptual understanding.
3. Metacognitive Planning – Students explicitly formulated problem-solving plans before executing procedures.
4. Metacognitive Monitoring and Reflection – During and after problem-solving, students monitored their reasoning, identified errors, and evaluated strategy effectiveness.
5. Reflective Consolidation – The teacher facilitated guided reflection discussions linking strategies, challenges, and emotional responses to learning.

The teacher's role in this group was as a facilitator and metacognitive scaffold provider, prompting students with reflective questions such as "Why did you choose this strategy?" and "How do you know your answer is correct?"

Control Group: Conventional Instruction
The control group received teacher-centered instruction characterized by explanation of procedures, worked examples, and individual practice exercises. Reflection and metacognitive prompts were not systematically incorporated.

Treatment Fidelity
To ensure treatment fidelity, the researchers developed a structured lesson plan manual and an implementation checklist. Each session was observed by an independent observer using a fidelity rubric to verify adherence to the instructional model. The average fidelity score across sessions was above 85%, indicating high consistency in implementation.

Data Collection

Post-test data were collected using a closed-ended Mathematical Resilience Questionnaire consisting of 20 items measuring four dimensions: (a) value; (b) struggle; (c) growth; and (d) perseverance (Kooken et al., 2015). Responses were measured using a four-point Likert scale.

Table 2. Mathematical Resilience Assessment Scale

Positive Statement		Negative Statement	
Criteria	Score	Criteria	Score
Strongly agree	4	Strongly agree	1
Agree	3	Agree	2
Disagree	2	Disagree	3
Strongly disagree	1	Strongly disagree	4

Table 2 presents the assessment scale used to evaluate students' mathematical resilience based on their responses to positive and negative statements. The scores obtained from the questionnaire reflect students' awareness of value, struggle, growth, and perseverance in facing mathematical challenges. The resulting data allow researchers to quantitatively interpret students' mathematical resilience and to conduct further analysis on differences between groups.

Data Analysis

1. Measurement Model Evaluation (CFA using PLS-SEM)
Confirmatory Factor Analysis (CFA) was conducted using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach with SmartPLS 4.0 software (Hair et al., 2019). PLS-SEM was selected for three main reasons: (1) the model involves latent constructs measured by multiple indicators; (2) the primary objective was prediction and variance explanation rather than model fit comparison; and (3) the sample size (n = 120) is relatively moderate, making PLS-SEM more appropriate than covariance-based SEM, which typically requires larger samples and multivariate normality assumptions.

The evaluation included:

- Convergent validity (outer loadings > 0.70; AVE > 0.50)
- Discriminant validity (Fornell–Larcker criterion; HTMT < 0.90)
- Construct reliability (CR and CA > 0.70)

Table 3. Convergent Validity and Construct Reliability

Dimension	Item	Outer Loadings	AVE	CR	CA
Value	S1	0,838	0,895	0,923	0,705
	S2	0,775			
	S3	0,855			
	S4	0,857			
	S5	0,870			

Struggle	S6	0,873	0,918	0,938	0,753
	S7	0,861			
	S8	0,895			
	S9	0,863			
	S10	0,846			
Growth	S11	0,834	0,892	0,921	0,699
	S12	0,822			
	S13	0,861			
	S14	0,828			
	S15	0,836			
Perseverance	S16	0,868	0,915	0,936	0,745
	S17	0,872			
	S18	0,858			
	S19	0,869			
	S20	0,848			

Table 3 shows that all indicators across each dimension have outer loading values above 0.70, thereby meeting the criteria for convergent validity and demonstrating that the indicators strongly reflect their respective constructs. The Average Variance Extracted (AVE) values for each dimension exceed the minimum threshold of 0.50, indicating that a substantial proportion of the indicators' variance is well explained by the latent constructs. The Composite Reliability (CR) and Cronbach's Alpha (CA) values are also above 0.70, suggesting that the instrument has very good internal consistency.

Table 4. Discriminant Validity

Dimension	Fornell-Larcker	HTMT
Value → Struggle	0,401	0,437
Value → Growth	0,398	0,444
Value → Perseverance	0,321	0,352
Struggle → Growth	0,365	0,399
Struggle → Perseverance	0,521	0,564
Perseverance → Growth	0,552	0,608

Table 4 shows that the dimensions meet the established criteria based on the two testing approaches employed. All values under the Fornell–Larcker criterion are below the required maximum correlation threshold, indicating that each construct demonstrates an adequate level of distinctiveness. Testing using the HTMT approach also produced values below the 0.90 cutoff, suggesting that there is no issue of overlap among the dimensions. The relationships among the constructs are categorized as low to moderate, further confirming that each dimension measures a conceptually distinct construct. These findings provide evidence that the measurement model has a clear structural configuration and is appropriate for subsequent structural analysis.

The next stage involved conducting a t-test to determine whether there was a significant difference in students' academic resilience between the group receiving metacognitive-based deep learning instruction and the control group. The effect size of the treatment was then analyzed using Cohen's d to assess the strength of the intervention's impact on improving students' academic resilience. The analysis concluded with a two-way ANOVA to examine the effects of the treatment and other factors simultaneously, as well as to explore potential interactions among the variables studied. All analytical procedures were conducted in accordance with proper methodological principles to ensure the validity, reliability, and scientific rigor of the research findings.

2. Independent Samples t-Test
An independent samples t-test was conducted to examine whether there was a statistically significant difference in academic resilience scores between the experimental and control groups. Prior to conducting the t-test, assumptions of normality (Shapiro–Wilk test) and homogeneity of variance (Levene's test) were evaluated. The t-test was chosen because the study aimed to compare the mean resilience scores of two independent groups after treatment.

3. Effect Size (Cohen's d)
Cohen's d was calculated to determine the magnitude of the treatment effect. Effect size interpretation followed conventional benchmarks (0.20 = small; 0.50 = medium; 0.80 = large). Given that educational interventions rarely produce extremely large effect sizes, the magnitude of the obtained effect was interpreted cautiously and further discussed in relation to contextual and methodological factors.

4. Two-Way ANOVA
A two-way ANOVA was conducted to examine (1) the main effect of instructional model (experimental vs control), (2) the main effect of grade level (fourth vs fifth grade), and (3) the interaction effect between instructional model and grade level.

The use of two-way ANOVA was justified because:

- The study involved two categorical independent variables (instructional model and grade level).
- It allowed simultaneous testing of main and interaction effects.
- It controlled for potential confounding effects of grade level on resilience outcomes.

Assumptions of normality, homogeneity of variance, and independence were tested prior to analysis. All statistical analyses were conducted using appropriate procedures to ensure methodological rigor, internal validity, and reliability of the findings.

RESULT

Descriptive statistical analysis was conducted to provide an overview of the distribution of post-test scores in both research groups after the treatment was administered. Information on the number of participants, score range, mean, and standard deviation was presented concisely to illustrate the quantitative tendencies of the data. This presentation served as an initial basis for identifying differences in learning outcome characteristics between the experimental and control groups before proceeding to inferential analysis. A summary of the descriptive statistical results is presented in Table 5.

Table 5. Result of the Descriptive Statistics

Group	N	Minimum	Maximum	Mean	Std. Deviation
Grade 4 Experiment	30	56.00	90.00	73.86	7.83
Grade 5 Experiment	30	63.00	89.00	76.63	6.79

Grade 4 Control	30	39.00	64.00	49.06	5.88
Grade 5 Control	30	41.00	66.00	52.96	6.75

Table 5 shows that the academic resilience achievement of students in the experimental group tended to be higher than that of the control group at both grade levels, with the mean score of Grade 5 in the experimental group reaching 76.63 and Grade 4 in the experimental group reaching 73.86, while in the control group the mean scores were 52.96 for Grade 5 and 49.06 for Grade 4. This difference indicates that the implementation of the treatment contributed positively to the improvement of students' academic performance, supported by a relatively stable distribution of data across all groups, suggesting that the score variation remained within a reasonable range. The substantial mean difference between groups demonstrates a clear performance gap between the experimental and control classes at both Grade 4 and Grade 5 levels, thus these descriptive findings provide a strong basis for further analysis through inferential testing as presented in Table 6.

Table 6. Result of the Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means					95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Post-test scores	Equal variances assumed	1.802	.182	18.945	118	.000	24.233	1.279	21.700	26.766
	Equal variances not assumed			18.945	116.404	.000	24.233	1.279	21.699	26.766

Table 6 indicates that the assumption of homogeneity of variance has been met, allowing the interpretation to use the equal variances assumed model. The significance value below the 0.05 threshold indicates a highly significant difference between the compared groups in the post-test scores. The mean difference of 24.233 points demonstrates that the treatment provided had a strong impact on improving students' learning outcomes. The 95% confidence interval, which lies entirely in the positive direction, further confirms that the difference is consistent and not due to chance. These findings are reinforced by the effect size calculation results presented in Table 7.

Table 7. Result of the Effect Size Cohen's D

Formula	Description
Cohen's d formula	$d = \frac{M_1 - M_2}{SD_{pooled}}$
Pooled SD formula	$SD_{pooled} = \sqrt{\frac{SD_1^2 + SD_2^2}{2}}$
Mean of Group 1 (M_1)	72.25
Mean of Group 2 (M_2)	51.01
SD of Group 1 (SD_1)	7.405
SD of Group 2 (SD_2)	6.583

Pooled SD (SD pooled)	$\sqrt{\frac{7.405^2 + 6.583^2}{2}} = 7.006$
Mean Difference (M_1 - M_2)	$72.25 - 51.01 = 24.24$
Cohen's d (d)	$d = \frac{24.24}{7.006} = 3.46$

Table 7 shows that the Cohen's d effect size value of 3.46 falls into the very large category, indicating a very strong treatment effect on the differences in outcomes between the two groups. This magnitude demonstrates that the intervention was able to produce a substantial improvement in learning outcomes compared to the comparison group. Interpretatively, the value of 3.46 is far above the common benchmark of 0.80 as the threshold for a large effect size, leading to the conclusion that the effect of the treatment on the studied variable is at a very high level of effectiveness. This finding is also consistent with the results of the analysis presented in Table 8.

Table 8. Result of the Two-Way ANOVA

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	17704.971[a]	3	5901.657	122.708	.000
Intercept	474093.568	1	474093.568	9857.374	.000
Group	17489.432	1	17489.432	363.641	.000
Class	224.748	1	224.748	4.673	.033
Group × Class	37.012	1	37.012	.770	.382
Error	5530.962	115	48.095		
Total	499208.000	119			
Corrected Total	23235.933	118			

Table 8 indicates that the overall model is statistically significant in explaining the variation in students' academic resilience scores, with a significance value of 0.000 (< 0.01). The learning group factor exerts a very strong effect on differences in students' scores, as reflected by an F value of 363.641 and a significance level of 0.000, suggesting that the instructional treatment makes a substantial contribution to improving the outcomes. The class factor also shows a significant effect, with a significance value of 0.033 (< 0.01), indicating a difference in scores between Grade 4 and Grade 5 students. However, the interaction between group and class does not demonstrate a significant effect, with a significance value of 0.382 (> 0.01), implying that the treatment effect tends to be consistent across both grade levels. The error value of 48.095 indicates that the within-group variation is relatively well controlled, thereby reinforcing the conclusion that the learning model is the dominant factor in enhancing students' academic resilience.

DISCUSSION

The implementation of the Metacognitive-Based Deep Learning model in mathematics learning demonstrates a highly significant impact on improving the academic resilience of elementary school students. The descriptive findings in Table 5 confirm that the experimental groups in Grade 4 and Grade 5 consistently achieved substantially higher mean scores than the control groups, indicating a clear performance gap between the groups. This advantage stems from the application of metacognitive strategies that enable students to monitor, evaluate, and regulate their thinking processes when facing complex mathematical tasks (Rivas et al., 2022).

The deep learning approach facilitates a more profound conceptual understanding, allowing students not merely to memorize formulas but to connect mathematical concepts with real-life situations, which in turn enhances their confidence in problem solving (Bakar et al., 2024). The results of the Independent Samples Test in Table 6 further strengthen these findings, with a significance value of 0.000 indicating a highly significant difference in performance between the two groups. The mean difference of 24.233 points reflects that the instructional intervention provided a stronger stimulus in developing students' learning resilience compared to conventional methods (Wadi et al., 2024). Students with a high level of metacognitive awareness tend to interpret failure in solving mathematical problems as an opportunity to develop new strategies rather than as a permanent obstacle in the learning process (Filiz & Gür, 2025).

The effectiveness of the intervention is further emphasized by the Cohen's d value of 3.46 in Table 7, which falls into the very large effect category. This magnitude indicates that the metacognition-based learning model possesses exceptionally high practical power in transforming elementary students' learning behaviors in a measurable and meaningful way (Drigas et al., 2023). The Two-Way ANOVA analysis presented in Table 8 provides additional insight into the consistency of the model's impact across grade levels. Although significant differences were found between Grade 4 and Grade 5 scores, no significant interaction was identified between the group factor and grade level (Luo et al., 2021). This condition indicates that the Metacognitive-Based Deep Learning model is adaptive and can be effectively implemented in both lower and upper elementary grades (Widiana et al., 2024).

A learning environment that promotes self-reflection contributes to the development of persistence and emotional regulation, which are fundamental components of academic resilience (Al-Rashidi & Aberash, 2024). The integration of deep conceptual understanding and self-regulation skills forms a psychological defense mechanism that helps students cope with mathematics anxiety commonly experienced at the elementary level (Mati et al., 2026). These findings are consistent with social constructivist theory, which positions active engagement and reflection as central elements in the process of knowledge acquisition (Le & Nguyen, 2024). The substantial increase in academic resilience demonstrates that pedagogical factors play a dominant role in shaping students' learning mindsets alongside individual internal factors (Afzali et al., 2024).

The application of metacognitive strategies in mathematics learning facilitates problem-solving processes through systematic planning, process monitoring, and independent evaluation of outcomes (Ukobizaba et al., 2021). The contribution of this study lies in strengthening empirical evidence that elementary mathematics curricula should place greater emphasis on thinking processes rather than merely focusing on final achievement outcomes (Mcdonald & Smith, 2020). This study has limitations, as it was conducted within a relatively short time frame and did not explore other potential mediating variables such as students' intrinsic motivation. These limitations provide opportunities for future research to examine the long-term impact of this learning model on memory retention and the development of students' academic character. Recommendations for subsequent studies include expanding the sample across diverse geographical regions to ensure stronger and more representative generalization of the findings.

CONCLUSION

This study demonstrates that the Metacognitive-Based Deep Learning model has a positive and highly significant effect on improving the academic resilience of elementary school students in mathematics learning. The consistent performance differences between the experimental and control groups in Grades 4 and 5, accompanied by a very large effect size, indicate the strength of the intervention both practically and statistically. The advantage of the model lies in the integration of metacognitive strategies that enhance reflection, self-regulation, and emotional resilience when students face complex mathematical problems. The theoretical contribution of this study emphasizes the importance of the deep learning approach in developing non-cognitive aspects during the critical phase of elementary education. Limitations related to the geographical scope and duration of the intervention require that generalization be undertaken cautiously; therefore, future research is recommended to involve broader samples and explore mediating variables such as intrinsic motivation in order to enrich understanding of the dynamics of academic resilience.

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