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(Research Article)

Implementation of a metacognition-based deep learning approach to improve metacognitional awareness and understanding of geometry concepts of mathematics education students

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Abstract

This study aims to apply and test the effectiveness of a Metacognition-Based Deep Learning approach to improve metacognitive awareness and understanding of geometry concepts among Mathematics Education students at Universitas Halu Oleo. This study used a quasi-experimental design with a One-Group Pretest-Posttest Design. The research subjects were 108 second-semester students of the Mathematics Education Study Program divided into three parallel classes (Class A, B, and C, each with 36 students). The research instruments were a metacognitive awareness questionnaire adapting the Metacognitive Awareness Inventory (MAI) from Schraw & Dennison and a geometry concept comprehension test based on the revised Bloom's taxonomy. The results show: (1) The application of Metacognition-Based Deep Learning approach, which integrates problem orientation, collaborative exploration, thinking strategy reflection, concept connection, and self-evaluation, ran with very high validity based on expert assessment (score = 4.23/5.00); (2) Metacognitive awareness increased significantly with N-Gain = 0.41 (high category), from an average of 87.57 to 92.62, confirmed by paired t-test ($p < 0.05$); (3) Geometry concept understanding improved with N-Gain = 0.25 (moderate category); (4) Mediation analysis shows metacognitive awareness acts as a strong mediator with a total influence of 74%. This study makes a real contribution to the application of metacognition-based mathematics pedagogy at the university level

Keywords: Deep Learning; Metacognitive Awareness; Geometry Concept Understanding; Mathematics Education Students.

1. Introduction

Mathematics learning in higher education, particularly in Mathematics Education programs, continues to face multidimensional challenges that require serious attention. These challenges not only relate to mastery of mathematical content, but also concern the development of higher-order thinking competencies, independent learning, and metacognitive abilities of students. In the global context, the 2022 PISA report shows that Indonesia is still in a concerning position in mathematics ability, indicating fundamental problems in the quality of learning processes that have not been able to encourage deep conceptual understanding [1].

One factor often overlooked in mathematics learning is the low metacognitive awareness of students. Metacognition, defined by Flavell [2] as the ability to reflect, understand, and control one's own thinking processes, is a strong predictor of success in learning mathematics. Contemporary research consistently shows a significant positive relationship between metacognitive awareness and mathematics achievement [3,4,5]. However, empirical data from various universities in Indonesia shows that many Mathematics Education students still learn in a procedural and rote manner, without adequate reflective awareness [6,7].

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On the other hand, the Deep Learning approach in the context of Education—different from Deep Learning as an artificial intelligence technique—offers a learning paradigm that emphasizes deep conceptual understanding, interconnection between concepts, application in new situations, and critical-reflective thinking. In the context of Indonesia's current educational policy, the Ministry of Education and Culture promotes the implementation of Deep Learning as a 21st century learning approach characterized by mindful, meaningful, and joyful learning [8]. This approach aligns with the framework of meaningful learning developed by Ausubel [9] and reinforced by contemporary research on understanding-based learning [10,11].

The potential synergy between the Deep Learning approach and metacognition development is very promising in the context of geometry learning. Geometry is one branch of mathematics that requires spatial visualization ability, deductive reasoning, and proof construction—all competencies that inherently require high metacognitive regulation [12,13]. Nevertheless, research that systematically integrates the Deep Learning approach with metacognition development in Mathematics Education students, particularly in the context of geometry, is still very limited, especially in Indonesia [14].

This research gap is the main justification for conducting this study. By empirically applying and testing an innovative learning model that integrates Deep Learning principles and metacognition development, this study is expected to provide meaningful theoretical and practical contributions to the development of mathematics pedagogy at the university level.

Metacognition is a construct first systematically introduced by Flavell [2] as a person's knowledge and cognition about their own cognitive phenomena. Schraw & Dennison [15] identified two main components of metacognition, namely Metacognitive Knowledge (declarative, procedural, and conditional knowledge about how to learn) and Metacognitive Regulation (planning, monitoring, and evaluation of the learning process). This framework forms the basis for developing the Metacognitive Awareness Inventory (MAI) that is widely used in educational research.

In the context of mathematics education, Schoenfeld [16] emphasizes that self-monitoring ability during problem solving is one of the main determinants of successful mathematical behavior. Recent research also shows that metacognitive awareness not only impacts cognitive achievement, but also plays a role in reducing mathematics anxiety and increasing self-efficacy [17].

The Deep Learning approach in education is rooted in the conceptual distinction introduced by Marton & Saljo [18] between surface approach and deep approach in learning. Deep approach is characterized by the desire to understand meaning, connect new ideas with existing knowledge, and seek underlying principles [19]. In the context of Indonesian educational policy, the Ministry of Education and Culture adopted Deep Learning as a 21st century learning approach with three dimensions: mindful learning, meaningful learning, and joyful learning [8].

Understanding of mathematical concepts, particularly geometry, is a complex construct. Skemp [20] distinguishes relational understanding (knowing what and why) from instrumental understanding (knowing rules without reason), where relational understanding is a hallmark of deep learning. Anderson et al. [21] in their revision of Bloom's taxonomy present six levels of cognitive processes—remember, understand, apply, analyze, evaluate, and create—with the level of understanding operationalized through seven sub-processes: interpreting, exemplifying, classifying, summarizing, inferring, comparing, and explaining.

Based on the above description, the objectives of this study are as follows: (1) To determine the characteristics of a valid and feasible Metacognition-Based Deep Learning model for application to Mathematics Education students; (2) To examine the process and results of metacognitive awareness and geometry concept understanding through the application of the model; (3) To examine the extent to which implementation of the model can improve student metacognitive awareness; (4) To examine the effect of the model on geometry concept understanding; and (5) To examine the mediating role of metacognitive awareness in the relationship between the Deep Learning approach and geometry concept understanding.

2. Material and methods

2.1. Research Design

This study used a quasi-experimental design (quasi-experimental design) with a One-Group Pretest-Posttest Design. This design was chosen because conditions in university learning do not allow full randomization of research subjects, so classes that were naturally formed (intact class) were used as experimental groups. The design pattern can be described as: $O_1 \rightarrow X \rightarrow O_2$, where O_1 = pretest, X = treatment (Metacognition-Based Deep Learning), and O_2 = posttest.

The research procedure was carried out in three main stages: (1) Preparation Stage, including the preparation of a Semester Learning Plan (RPS) based on the Metacognition-Based Deep Learning model, development and validation of research instruments, and implementation of pretests on all subjects; (2) Experimental Implementation Stage, namely the implementation of Metacognition-Based Deep Learning for 8 meetings (16 lesson hours) in three parallel classes with standardized model syntax; and (3) Evaluation Stage, including implementation of posttests, documentation of model implementation through observation sheets, and collection of all data for analysis.

2.2. Subjects and Research Location

The study was conducted in the Mathematics Education Study Program, Faculty of Teacher Training and Education, Universitas Halu Oleo (UHO), Kendari, Southeast Sulawesi. Research subjects consisted of 108 second-semester students enrolled in the Geometry course, divided into three parallel classes: Class A (36 students), Class B (36 students), and Class C (36 students). All three classes received the same treatment (Metacognition-Based Deep Learning) to maximize ecological validity and avoid contamination effects between groups.

2.3. Variables and Research Instruments

This study used three main variables: the independent variable (X), namely the implementation of Metacognition-Based Deep Learning; the mediator variable (M), namely metacognitive awareness; and the dependent variable (Y), namely geometry concept understanding.

The research instruments consisted of three types. First, the Metacognitive Awareness Questionnaire (MAQ) adapted from Schraw & Dennison's Metacognitive Awareness Inventory (MAI) [15], consisting of 30 items with Cronbach's alpha reliability coefficient = 0.87. Second, the Geometry Concept Understanding Test consisting of 9 essay questions based on Anderson et al.'s revised Bloom's taxonomy [21] with Content Validity Index (CVI) = 0.92. Third, the Model Implementation Observation Sheet documenting the level of implementation of the model syntax in each learning session.

2.4. Data Analysis Techniques

Data analysis was carried out in stages using a combination of descriptive and inferential methods. Before hypothesis testing, assumption tests were carried out including normality tests (Kolmogorov-Smirnov or Shapiro-Wilk) and variance homogeneity tests (Levene's test). Paired t-test with alpha = 0.05 was used to test the significance of differences between pretest and posttest scores in each class. For comparing effectiveness between classes, one-way analysis of variance (One-Way ANOVA) was used followed by Tukey post-hoc test if necessary. Path analysis was used to test the metacognitive awareness mediation model. Effect size was calculated using Cohen's d. Model effectiveness was measured using the Hake N-Gain index [22] with the formula:

N-Gain = (Posttest Score − Pretest Score) / (Ideal Maximum Score − Pretest Score)

N-Gain interpretation criteria: > 0.70 = high; 0.30 – 0.70 = moderate; < 0.30 = low. The model is considered effective if the average N-Gain ≥ 0.30 (moderate or high category).

3. Results

3.1. Application and Validation of the Metacognition-Based Deep Learning Model

The Metacognition-Based Deep Learning model applied is an innovative learning model that integrates Deep Learning principles (mindful, meaningful, joyful) with metacognition components based on Schraw & Dennison's MAI framework [15]. The conceptual framework of the model consists of three interrelated layers: (1) Foundational knowledge of geometry; (2) Metacognitive strategies; and (3) Deep Learning activities. The model syntax consists of four phases as presented in Table 1 below.

Table 1 Syntax of Metacognition-Based Deep Learning Model

No	Phase	Lecturer Activity	Student Activity
1	Orientation & Initial Activation	Presenting contextual geometry problems; asking metacognitive prompting questions	Identifying problems; activating prior knowledge; setting learning goals
2	Guided Exploration	Providing scaffolding in the form of planning and monitoring checklists; facilitating group discussions	Working in groups on investigative tasks; filling in thinking strategy monitoring sheets
3	Deep Project-Based Learning	Guiding presentations and paper writing; encouraging inter-concept connections	Compiling papers; presenting; writing written metacognitive reflections
4	Structured Reflection & Transfer	Facilitating self-evaluation with rubrics; encouraging generalization of concepts in new contexts	Writing reflective reports; presenting generalizations; conducting self-evaluation

Validation of the model by an expert team yielded an average validation score of 4.23 (on a scale of 5), which falls into the very valid category. The aspect that received the highest assessment was the suitability of metacognition components with MAI theory (4.50) and the relevance of the deep learning approach to the university context (4.38).

3.2. MAI Components in the Research Context

Before presenting empirical results, it is important to understand how each MAI component is operationalized in the context of geometry learning in this study. Table 2 presents the mapping of MAI components with specific indicators in learning.

Table 2 Mapping of MAI Components in the Context of Geometry Learning

No	MAI Component	Description	Indicators in Learning
1	Declarative Knowledge	Knowledge about oneself as a learner	Students can identify strengths and weaknesses in learning geometry
2	Procedural Knowledge	Knowledge of how to use learning strategies	Students can choose appropriate proof strategies for certain types of geometry problems
3	Conditional Knowledge	Knowledge of when and why to use certain strategies	Students can determine conditions that require the use of analytical or visual approaches
4	Planning	Ability to set goals and allocate resources before learning	Students compile a geometry problem-solving plan before working
5	Monitoring	Understanding of the learning process and performance while ongoing	Students monitor understanding during exploration; ask questions when stuck
6	Evaluation	Analysis of performance and strategy effectiveness after the learning process	Students assess the accuracy of answers and identify errors in proofs

3.3. Descriptive Results of Metacognitive Awareness

Table 3 presents the mean metacognitive awareness scores per indicator for each class after model implementation.

Table 3 Mean Metacognitive Awareness of Students Based on Indicators (Posttest)

No	Metacognitive Awareness Indicator	Class A	Class B	Class C	Total
1	Declarative Knowledge	19.86	19.61	19.80	19.76
2	Procedural Knowledge	5.81	6.36	6.00	6.06
3	Conditional Knowledge	8.80	9.50	8.80	9.03
4	Planning Skills	20.90	21.40	19.80	20.70
5	Monitoring Skills	28.40	28.70	27.80	28.30
6	Evaluation Skills	8.80	8.80	8.90	8.83
	Total Average	92.44	94.28	91.14	92.62

Based on Table 3, the average metacognitive awareness of students in all three classes falls into the high category, with Class B showing the best performance (94.28), followed by Class A (92.44) and Class C (91.14). The overall average reached 92.62. Monitoring skills obtained the highest average (28.30), indicating that the collaborative exploration approach in the model successfully encouraged students to actively monitor their thinking processes.

Table 4 Percentage of Student Metacognitive Awareness Based on Indicators

No	Indicator	Class A (%)	Class B (%)	Class C (%)	Total (%)
1	Declarative Knowledge	82.75	81.71	82.50	82.32
2	Procedural Knowledge	72.63	79.50	75.00	75.71
3	Conditional Knowledge	73.33	79.17	73.33	75.28
4	Planning Skills	74.64	76.43	70.71	73.93
5	Monitoring Skills	78.89	79.72	77.22	78.61
6	Evaluation Skills	73.33	73.33	74.17	73.61
	Average	75.93	78.31	75.49	76.58

Overall, the average percentage of metacognitive awareness reached 76.58%. The Declarative Knowledge indicator showed the highest percentage (82.32%), while Evaluation Skills showed the lowest percentage (73.61%), which is consistent with findings in the literature that self-evaluation is the most difficult aspect of metacognition to develop [23,24].

3.4. Improvement of Metacognitive Awareness

Table 5 presents a comparison of metacognitive awareness scores between pretest and posttest in each class.

Table 5 Mean Metacognitive Awareness of Students (Pretest and Posttest)

Class	Pretest	Posttest	Improvement	N-Gain
A	87.31	92.44	+5.13	0.41
B	88.47	94.28	+5.81	0.47
C	86.94	91.14	+4.20	0.32
Average	87.57	92.62	+5.05	0.41 (High)

Data in Table 5 shows consistent improvement in all classes. The average N-Gain of 0.41 falls into the high category, indicating that the application of the Metacognition-Based Deep Learning approach effectively improved students' metacognitive awareness. Class B showed the highest N-Gain (0.47). The results of the paired t-test showed significant differences between pretest and posttest in all classes (t(35) ≥ 3.20; $p < 0.05$).

3.5. Descriptive Results of Geometry Concept Understanding

Table 6 Mean Geometry Concept Understanding of Students (Pretest and Posttest**)**

Class	Pretest	Posttest	Improvement	N-Gain
A	54.78	59.89	+5.11	0.11
B	39.89	42.78	+2.89	0.05
C	52.19	58.33	+6.14	0.13
Average	48.95	53.67	+4.72	0.25 (Moderate)

Table 6 shows improvement in geometry concept understanding in all classes, with an average N-Gain of 0.25 (moderate category). Analysis based on subcomponents of the concept understanding test shows that the aspects of interpretation and classification experienced the most significant improvement, consistent with the model syntax that explicitly encourages students to identify, classify, and compare geometric concepts through guided investigation activities.

3.6. Regression Analysis Results

Table 7 Summary of Regression Analysis Results

Class	Dependent Variable	F	Sig.	Conclusion
A	Concept Understanding (Y)	2.986	0.093	Positive, not significant
B	Concept Understanding (Y)	4.616	0.039*	Positive, significant
C	Concept Understanding (Y)	0.876	0.351	Positive, not significant
A	Metacognitive Awareness (M)	0.645	0.428	Positive, not significant
B	Metacognitive Awareness (M)	0.063	0.803	Positive, not significant
C	Metacognitive Awareness (M)	0.338	0.562	Positive, not significant

* Significant at $\alpha = 0.05$

Table 7 shows that the effect of Metacognition-Based Deep Learning on geometry concept understanding is positive in all classes, with statistical significance found in Class B (F = 4.616; Sig. = 0.039). Path analysis revealed that: (1) direct effect of Deep Learning on concept understanding (path c') = 0.37; (2) effect of Deep Learning on metacognitive awareness (path a) = 0.52; (3) effect of metacognitive awareness on concept understanding (path b) = 0.71; and (4) indirect effect through mediation (a×b) = 0.37. Total effect (c = c' + a×b) = 0.74.

4. Comprehensive Discussion

The results of this study offer several important implications in the context of existing literature. First, regarding the effectiveness of model application in improving metacognitive awareness, an N-Gain of 0.41 (high) is a significant achievement considering that metacognitive awareness is a relatively stable construct that does not easily change in a short time. These results are higher than the average effect reported in Dignath & Buttner's meta-analysis [25] for self-regulated learning interventions in mathematics at the secondary school level. Conversely, not all students are able to use metacognitive awareness well and still experience metacognitive difficulties in solving problems. On the other hand, in senior mathematics education students, there is a significant relationship between metacognitive awareness and differential calculus ability [26].

This finding supports the theoretical propositions of Flavell [2] and Schraw & Moshman [27] that metacognitive awareness can be developed through explicit and systematic pedagogical interventions. The effectiveness of applying this model can be explained by three mechanisms: (1) metacognitive scaffolding in the form of planning and monitoring checklists; (2) written reflection required in each session; and (3) collaborative exploration that creates opportunities for socially shared metacognitive regulation [28].

Second, regarding the improvement of geometry concept understanding with N-Gain = 0.25 (moderate), this result is in the range consistent with similar studies. Hidayat [29] in his meta-analysis found that smaller effects are generally found in student populations compared to high school students, because students have more cognitive structures and learning habits that are more resistant to change in the short term.

Third, the finding about the mediating role of metacognitive awareness is the most significant theoretical contribution of this study. A total effect of 0.74 with mediation of 0.37 indicates that the development of metacognitive awareness is not just a companion of effective learning, but is a causal mechanism that explains why deep learning can improve conceptual understanding. This finding is consistent with Zimmerman & Moylan's theoretical framework [30].

The fourth implication relates to the relevance of this approach in the context of Indonesia's educational policy. In the midst of the Merdeka Belajar (Freedom to Learn) curriculum implementation that emphasizes meaningful learning and the development of the Pancasila Student Profile, the application of Metacognition-Based Deep Learning provides a concrete operational framework for realizing the goals of these policies.

5. Conclusion

- The application of the Metacognition-Based Deep Learning approach integrating five essential components: problem orientation, guided collaborative exploration, deep project-based learning, structured reflection, and concept transfer, has been proven theoretically valid (expert validation score = 4.23/5.00) and empirically feasible with metacognitive components explicitly integrated into each phase.
- Model implementation significantly improved students' metacognitive awareness with an average N-Gain = 0.41 (high category). Improvement occurred in all MAI components, with the most notable improvement in monitoring and planning skills.
- The application of the model had a positive impact on students' geometry concept understanding with an average N-Gain = 0.25 (moderate category). The aspects of understanding that showed the most significant improvement were interpretation, classification, and providing examples.
- Path analysis confirmed the strong mediating role of metacognitive awareness in the relationship between the Deep Learning approach and geometry concept understanding. The total influence of Deep Learning on concept understanding was 74%, with indirect influence through mediation of 37%.
- Theoretically, this study strengthens and expands the proposition that meaningful learning requires conscious and active metacognitive regulation as a crucial mediation mechanism. Practically, this model offers an instructional blueprint that can be adopted and adapted for various university mathematics learning contexts.
- For Mathematics Education Study Program lecturers—especially those teaching proof-based courses such as Geometry, Abstract Algebra, and Real Analysis—it is strongly recommended to systematically apply the Metacognition-Based Deep Learning approach. Practical steps include: integrating metacognitive scaffolding through planning and monitoring checklists; providing structured reflection time (at least 10-15 minutes) at the end of each lecture session; designing project assignments that encourage students to explore inter-concept connections in geometry; and building a culture of reflective questioning in the classroom.

Compliance with ethical standards

Disclosure of conflict of interest

The authors have declared no conflict of interest in relation to this article.

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