Examining the Effectiveness of Multiple Representation (SiMaYang) Learning Model on Students' Mathematical Conceptual Understanding: The Role of Self-Efficacy

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Article Info

Article history:

Received Apr , 2026
Revised Apr 14, 2026
Accepted Apr 30, 2026
Online First May 13, 2026

Keywords:

Learning Effectiveness
Mathematical Conceptual Understanding
Multiple Representation (SiMaYang) Learning Model
Self-Efficacy

ABSTRACT

Purpose of the study: This study aims to examine the effectiveness of the Multiple Representation (SiMaYang) learning model on students' mathematical conceptual understanding and to determine the role of students' self-efficacy in influencing differences in conceptual understanding outcomes.

Methodology: This study employed a quantitative approach with a quasi-experimental method using a 2×3 factorial design. Data were collected using essay tests and Likert-scale questionnaires. Statistical analysis included Liliefors normality test, Bartlett homogeneity test, independent t-test, and two-way ANOVA with unequal cells, followed by Scheffé test using statistical software.

Main Findings: Results showed that the SiMaYang learning model produced higher mathematical conceptual understanding than conventional learning. Self-efficacy significantly affected students' conceptual understanding, where high self-efficacy students performed better than others. No interaction effect was found between learning model and self-efficacy. SiMaYang model consistently improved understanding across all self-efficacy levels, indicating independent contributions of instructional model and affective factors.

Novelty/Originality of this study: This study integrates cognitive and affective aspects by simultaneously examining the effect of the SiMaYang learning model and self-efficacy within a single analytical framework. It provides a more comprehensive understanding of learning effectiveness by using factorial design analysis, offering new insights into how instructional strategies and internal beliefs independently influence mathematical conceptual understanding.

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1. INTRODUCTION

Mathematics learning plays an important role in developing students' logical thinking, reasoning, and problem-solving abilities. Through mathematics, students are expected not only to master procedures but also to understand concepts deeply [1]. Conceptual understanding becomes a key foundation for solving various mathematical problems and applying knowledge in real-life situations [2], [3]. However, learning mathematics is not only influenced by cognitive aspects but also by affective factors [4], [5]. One important factor that influences students' learning outcomes is self-efficacy.

Many students still experience difficulties in understanding mathematical concepts, especially when dealing with abstract material. Mathematics is often perceived as a difficult subject due to the presence of formulas and complex calculations. This condition leads to low student engagement and limited participation during the learning process [6], [7]. In addition, students' confidence in their own abilities tends to be low, which affects their performance in solving problems. As a result, students' conceptual understanding in mathematics remains unsatisfactory.

Previous studies have shown that the use of appropriate learning models can improve students' understanding of mathematical concepts. One of the learning approaches that has been widely discussed is the Multiple Representation (SiMaYang) learning model, which integrates various forms of representation [8]. Research indicates that this model can help students understand abstract concepts by connecting symbolic, visual, and contextual representations [9], [10]. In addition, self-efficacy has been proven to significantly influence students' learning outcomes in mathematics. Students with higher self-efficacy tend to show better performance and persistence in learning.

However, most previous studies tend to examine the effectiveness of learning models and self-efficacy separately. There is still limited research that investigates how the SiMaYang learning model interacts with students' self-efficacy in influencing conceptual understanding [11], [12]. This lack of integrated analysis creates a gap in understanding the combined effect of cognitive and affective factors. As a result, the relationship between instructional strategies and students' internal beliefs has not been fully explored [13], [14]. This condition highlights the need for further investigation in a more comprehensive manner.

Understanding the interaction between learning models and self-efficacy is important to improve the quality of mathematics learning. By identifying how students respond to different instructional approaches, teachers can design more effective and engaging learning environments [15], [16]. The use of appropriate learning models can also help students develop confidence in their abilities. In addition, improving conceptual understanding will support students in solving more complex mathematical problems [17]. Therefore, efforts to enhance both instructional strategies and self-efficacy are essential in mathematics education.

This study offers novelty by examining the effectiveness of the SiMaYang learning model on students' mathematical conceptual understanding by considering self-efficacy as a moderating factor. Unlike previous studies, this research integrates cognitive and affective aspects in one framework. It explores not only the effectiveness of the learning model but also how students' confidence influences learning outcomes. This approach provides a more comprehensive understanding of students' learning processes. Therefore, this study contributes to enriching knowledge in mathematics education and offers practical implications for teaching practices.

2. RESEARCH METHOD

2.1 Research Design

This study employed a quantitative approach using a quasi-experimental design [18], [19]. The research aimed to examine the effectiveness of the Multiple Representation (SiMaYang) learning model on students' mathematical conceptual understanding, considering the role of self-efficacy. A 2×3 factorial design was applied, involving two factors: learning model and students' self-efficacy.

Table 1. Factorial Research Design (2×3)

Learning Model	High Self-Efficacy (B1)	Medium Self-Efficacy (B2)	Low Self-Efficacy (B3)
SiMaYang (A1)	A1B1	A1B2	A1B3
Conventional (A2)	A2B1	A2B2	A2B3

2.2 Variables of the Study

This study involved two independent variables and one dependent variable:

Independent Variables:

1. Learning model (X_1):
   - 1 = SiMaYang
   - A2 = Conventional
2. Students' self-efficacy (X_2):
   - B1 = High
   - B2 = Medium
   - B3 = Low

Dependent Variable:

- Students' mathematical conceptual understanding (Y)

2.3 Population and Sample

The population of this study consisted of all eighth-grade students at SMP Negeri 25 Bandar Lampung, totaling 286 students. The sample was selected using simple random sampling, resulting in two classes:

- An experimental class taught using the SiMaYang model
- A control class taught using the conventional model

2.4 Data Collection Techniques

Data were collected using the following methods:

1. Test
   Used to measure students' mathematical conceptual understanding in the form of essay questions.
2. Questionnaire
   Used to assess students' self-efficacy using a Likert scale.
3. Interview
   Conducted with the mathematics teacher to obtain supporting information.
4. Documentation
   Used to collect relevant data about students and school conditions.

3. RESULTS AND DISCUSSION

3.1 Baseline Data and Assumption Testing

The initial ability of students was analyzed using their previous semester examination scores. Descriptive statistics for both groups are presented in Table 1.

Table 1. Descriptive Statistics of Students' Initial Ability

Group	N	Min	Max	Mean	SD
Control	31	20	80	46.06	13.32
Experimental	30	28	88	51.47	13.84

The experimental group shows a slightly higher mean score than the control group. However, further statistical testing is required to determine group equivalence.

- Normality Test (Liliefors)

Table 2. Normality Test Results

Group	Lmax	Ltable ($\alpha = 0.05$)	Decision
Control	0.14	0.16	Normal
Experimental	0.10	0.16	Normal

- Homogeneity Test (Bartlett)

Table 3. Homogeneity Test Results

χ^2count	χ^2table ($\alpha = 0.05$)	Decision
0.04	3.84	Homogeneous

- Balance Test (t-test)
  The balance test result shows:
  - tcount = 1.55
  - tcritical = ±2.00

Since tcountt is within the acceptance region, both groups are statistically equivalent before treatment.

3.2 Instrument Testing

Mathematical Concept Test

After validity and reliability testing:

- Valid items: 6 out of 8
- Reliability coefficient: 0.80 (high reliability)

Table 4. Summary of Instrument Testing

Item	Validity	Discrimination	Difficulty	Decision
1	Valid	Fair	Medium	Used
2	Invalid	Poor	Easy	Removed
3	Valid	Good	Medium	Used
4	Invalid	Poor	Easy	Removed
5	Valid	Fair	Easy	Used
6	Valid	Fair	Medium	Used
7	Valid	Fair	Hard	Used
8	Valid	Good	Medium	Used

Self-Efficacy Questionnaire

- Valid items: 32 out of 38
- Reliability coefficient: 0.90 (very high)

Thus, both instruments were considered valid and reliable for data collection.

3.3 Hypothesis Testing

Hypothesis testing was conducted using a two-way ANOVA with unequal cell sizes after all prerequisite assumptions were met. The results showed a significant effect of the learning model on students' mathematical conceptual understanding ($F = 5.07 > F_t = 4.02$), indicating that students taught using the SiMaYang model outperformed those in the conventional class. In addition, self-efficacy had a significant effect ($F = 6.02 > F_t = 3.17$), meaning that students with different levels of self-efficacy demonstrated different levels of conceptual understanding. However, no significant interaction effect was found between the learning model and self-efficacy ($F = 0.22 < F_t = 3.17$), suggesting that the effectiveness of the learning model is independent of students' self-efficacy levels.

Further analysis using the Scheffé test revealed that students with high self-efficacy performed significantly better than those with medium and low self-efficacy, while no significant difference was found between the medium and low groups.

3.4 Interpretation of Findings

The findings of this study indicate that the SiMaYang learning model is more effective than conventional learning in improving students' mathematical conceptual understanding, as reflected in the higher mean scores of the experimental group. In addition, self-efficacy plays a significant role, where students with higher self-efficacy demonstrate better conceptual understanding compared to those with medium and low levels [20], [21]. However, no significant interaction effect was found between the learning model and self-efficacy, suggesting that the effectiveness of the SiMaYang model is consistent across different self-efficacy levels. Overall, these results highlight that both instructional approach and self-efficacy independently contribute to students' mathematical learning outcomes.

Results show that implementation of SiMaYang learning model significantly improves students' mathematical conceptual understanding compared to conventional learning. Students taught using SiMaYang achieved higher mean scores, indicating better comprehension of mathematical concepts. Use of multiple representations helps learners connect abstract ideas with more concrete forms. Visual, symbolic, and contextual representations support construction of deeper understanding. Therefore, SiMaYang learning model can be considered an effective instructional strategy in mathematics learning.

Findings also indicate that self-efficacy has a significant influence on students' mathematical conceptual understanding. Students with high self-efficacy demonstrate better performance compared to those with medium and low levels. Confidence in personal ability plays an important role in determining learning outcomes. High self-efficacy encourages persistence and active engagement in problem solving. Consequently, affective factors such as self-efficacy are essential in supporting success in mathematics learning.

Findings align with previous studies highlighting effectiveness of multiple representation learning models in enhancing conceptual understanding. Earlier research shows that integration of various representations facilitates cognitive processing [22], [23]. Studies on self-efficacy also emphasize its contribution to academic performance and motivation. However, many previous studies examined these variables separately rather than within an integrated framework [24], [25]. Present study addresses that gap by analyzing learning model and self-efficacy simultaneously.

Novelty of study lies in integration of cognitive and affective factors within a single framework. Research not only evaluates effectiveness of SiMaYang model but also considers role of self-efficacy in influencing learning outcomes. Approach provides a more comprehensive perspective on students' learning processes [26]. Use of factorial design enables deeper analysis of main and interaction effects [27]. Findings contribute new insights to mathematics education research.

Implications of study are relevant for teachers and educational practitioners. Application of SiMaYang learning model is recommended to enhance conceptual understanding [28], [29]. Efforts to improve self-efficacy should also be integrated into classroom practices. Strategies such as positive reinforcement and active learning participation can strengthen students' confidence [30]. Integration of effective instructional strategies and psychological support can improve learning outcomes.

Several limitations should be acknowledged. Study focused only on specific topic, namely cubes and rectangular prisms, which may limit generalization. Sample was taken from a single school, reducing external validity [31], [32]. Research considered only two independent variables, while other factors such as motivation and learning styles were not included. Duration of treatment was relatively short. Future research is recommended to involve broader samples, longer interventions, and additional variables.

4. CONCLUSION

Findings of study confirm that application of SiMaYang learning model effectively improves students' mathematical conceptual understanding, aligning with initial objective stated in introduction. Results demonstrate that students taught using multiple representation approach achieve better conceptual comprehension compared to those experiencing conventional learning. In addition, self-efficacy is proven to play a significant role, where higher levels of confidence are associated with better learning outcomes. However, absence of interaction effect indicates that effectiveness of learning model operates independently from students' self-efficacy levels. These findings highlight importance of integrating appropriate instructional strategies with attention to students' psychological factors in mathematics education. Future research is recommended to explore broader mathematical topics, involve larger and more diverse samples, and examine additional variables in order to expand applicability and strengthen generalization of findings.

ACKNOWLEDGEMENTS

The author would like to express sincere gratitude to all parties who have supported completion of this study. Appreciation is extended to the school, teachers, and students who participated in data collection process. Special thanks are also addressed to academic supervisors for valuable guidance and constructive feedback throughout research process. In addition, gratitude is given to all contributors who provided support, both directly and indirectly. Financial support, if any, is also gratefully acknowledged.

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