

INTEGRATION OF COMPUTATIONAL THINKING IN MATHEMATICS LEARNING TO IMPROVE STUDENTS' MATHEMATICAL REASONING SKILLS

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Abstract

Although computational thinking has been increasingly integrated into mathematics education, empirical evidence of its contribution to students' mathematical reasoning remains limited, particularly at the junior secondary level. This study examined the effect of integrating computational thinking into mathematics learning on eighth-grade students' mathematical reasoning ability. A quasi-experimental method with a non-equivalent control group design was employed, involving 64 students at SMP N 4 Jakarta, divided equally into experimental and control classes. Data were collected through mathematical reasoning tests, student questionnaires, and classroom observations. Analyses included descriptive statistics, instrument quality tests, assumption tests, t-tests, N-Gain, effect size, and ANCOVA. The experimental class achieved a higher posttest mean score (82.28) than the control class (68.56). Their respective N-Gain scores were 0.645 and 0.373. The difference was statistically significant ($p < .001$), with a very large effect size (Cohen's $d = 2.073$). ANCOVA also confirmed a significant effect after controlling for initial ability. These findings suggest that computational thinking is an effective pedagogical approach for strengthening mathematical reasoning among junior secondary students.

Keywords: Computational thinking; mathematical reasoning; mathematics learning

INTRODUCTION

Mathematical reasoning ability is one of the essential competencies in mathematics learning because it enables students to connect concepts, construct arguments, identify patterns, formulate generalizations, and draw conclusions based on mathematical principles. Mathematical reasoning involves more than obtaining correct answers; it also requires students to explain their thinking processes, justify their strategies, and establish logical relationships between mathematical concepts. These competencies are particularly important in contemporary education, where students are expected to solve complex, open-ended, and contextual problems. Through mathematical reasoning, students can develop a deeper understanding of mathematical ideas and apply their knowledge to unfamiliar situations. Hidayat et al. (2022) emphasized the importance of mathematical reasoning in solving everyday

mathematical problems, while Mukuka et al. (2023) highlighted its relationship with conceptual understanding and the broader application of mathematical knowledge.

Despite its importance, mathematical reasoning remains a challenge in mathematics education, particularly at the junior secondary school level. Students may successfully follow procedures demonstrated by teachers but struggle when they encounter problems requiring analysis, pattern generalization, logical justification, or the development of alternative solutions. Such difficulties suggest that procedural fluency does not necessarily reflect a comprehensive understanding of mathematical concepts. When learning primarily emphasizes formula memorization and repetitive exercises, students may become dependent on familiar procedures and experience difficulties transferring their knowledge to non-routine problems. Consequently, mathematics instruction needs to provide more opportunities for students to explore mathematical relationships, explain their reasoning, and evaluate the validity of their solutions. Angraini et al. (2024) reported that junior high school students' mathematical reasoning ability remains inadequate, while Usman et al. (2026) indicated that students may rely on procedural strategies without sufficient conceptual understanding when addressing unfamiliar mathematical problems.

One potential approach to addressing these challenges is the integration of computational thinking (CT) into mathematics learning. Computational thinking refers to a systematic approach to problem solving that involves decomposing complex problems, recognizing patterns, abstracting relevant information, designing algorithms, and evaluating solutions. Although computational thinking is frequently associated with computer science and programming, its underlying principles are also relevant to mathematical learning. Students can apply decomposition to separate complex mathematical problems into manageable components, pattern recognition to identify relationships among numbers or geometric structures, and abstraction to distinguish essential information from irrelevant details. Algorithm design supports the development of coherent solution procedures, while evaluation encourages students to verify their reasoning and determine whether their answers are appropriate. These processes provide opportunities to develop mathematical reasoning through structured, explicit, and reflective problem-solving activities. Mendrofa (2024) explained that integrating computational thinking into mathematics can support problem-solving ability, logical reasoning, and systematic approaches to mathematical challenges.

The relationship between computational thinking and mathematical reasoning can be understood through their shared emphasis on logical processes, relationships, generalization, and justification. For example, when solving a problem involving numerical patterns, students can identify repeated relationships, formulate a general rule, and explain why the rule applies to subsequent cases. Similarly, when addressing problems involving area or volume, students can decompose the problem into smaller

components, identify relevant measurements, select appropriate mathematical relationships, and organize the calculation steps. These activities require students to interpret information, construct logical procedures, and evaluate the consistency of their conclusions. Computational thinking therefore offers a pedagogical framework through which mathematical reasoning can be practiced during the problem solving process rather than treated exclusively as an outcome measured after instruction.

Previous studies have increasingly examined the contribution of computational thinking to mathematics education. Research has associated CT integration with students' problem-solving ability, logical thinking, mathematical generalization, and systematic reasoning. Fauzi et al. (2024), through a systematic literature review, discussed the implications of computational thinking integration for mathematics education and student learning. Similarly, Isharyadi & Juandi (2023) emphasized the potential of computational thinking to support generalization, algorithmic thinking, logical reasoning, and the resolution of real-world mathematical problems. These findings suggest that CT may provide a useful foundation for learning activities that require students to analyze information, identify mathematical structures, and develop appropriate solution strategies. However, the extent to which these potential benefits translate into measurable improvements in mathematical reasoning requires further investigation through classroom-based empirical research.

The integration of computational thinking is also consistent with broader educational priorities associated with twenty-first-century competencies. Students increasingly need to demonstrate critical thinking, digital literacy, adaptability, and the ability to solve problems systematically. Mathematics education can contribute to these competencies by incorporating learning experiences that encourage students to explore multiple strategies, explain their decisions, and assess the effectiveness of their approaches. Mangiri & Prabawanto (2024) discussed developments in computational thinking research in mathematics learning, including the use of learning media, simulations, programming platforms, and visualization. Suarsana et al. (2024) likewise highlighted the growing attention given to computational thinking integration in mathematics education across different contexts. Nevertheless, the successful implementation of CT does not necessarily depend on programming activities alone. Its principles can also be embedded in conventional mathematics lessons through carefully designed tasks, structured reasoning activities, and opportunities for students to explain their problem-solving decisions.

Although the existing literature provides a foundation for integrating computational thinking into mathematics education, several issues remain relevant for further research. First, some studies emphasize the development of computational thinking skills themselves, whereas others focus primarily on mathematical problem-solving performance. These outcomes are related to mathematical reasoning but are not interchangeable. Problem solving concerns the process of finding solutions to

mathematical tasks, while mathematical reasoning places particular emphasis on the logical justification of procedures, the identification of relationships, the construction of arguments, and the validity of conclusions. Second, evidence about the direct contribution of CT-integrated instruction to mathematical reasoning among junior secondary students remains important, especially in classroom contexts where students are transitioning from procedural learning toward more abstract mathematical thinking. Obando Montoya et al. (2026) highlighted the need for further empirical investigation into CT-based learning strategies in mathematics education, while Husain et al. (2025) emphasized the importance of examining the implementation and educational impact of computational thinking. These concerns support the need for studies that directly assess mathematical reasoning outcomes rather than relying solely on related competencies.

The novelty of the present study lies in its explicit integration of computational thinking components into the stages of mathematics instruction and its empirical examination of students' mathematical reasoning ability. Rather than treating computational thinking as an additional subject or limiting it to programming activities, this study incorporates its principles into mathematics learning tasks. Students are guided to decompose problems, recognize patterns, abstract relevant information, construct systematic solution steps, and evaluate their answers. This instructional structure emphasizes both the mathematical outcomes and the reasoning processes through which students arrive at their conclusions. Furthermore, the study employs a quasi-experimental design involving experimental and control classes, enabling a comparative examination of learning outcomes and changes in students' performance. By examining mathematical reasoning directly, the research seeks to provide context-specific evidence concerning the educational value of computational thinking integration at the junior secondary level.

Based on this rationale, the present study aims to examine the effect of integrating computational thinking into mathematics learning on eighth-grade students' mathematical reasoning ability at SMP N 4 Jakarta. Specifically, it compares the mathematical reasoning outcomes of students who participate in CT-integrated mathematics instruction with those who receive instruction under the comparison condition. The findings are expected to contribute empirical evidence to discussions about computational thinking in mathematics education and inform the development of instructional strategies that promote logical reasoning, conceptual understanding, and systematic problem solving. In practical terms, this study may provide mathematics teachers with an alternative approach to designing classroom activities that encourage students to explain their reasoning, establish mathematical relationships, and evaluate the validity of their solutions. Ultimately, integrating computational thinking into mathematics learning may help create more active, reflective, and conceptually

meaningful learning experiences aligned with the demands of twenty-first-century education.

RESEARCH METHOD

This study uses a quasi-experimental method with *a non-equivalent control group design*. This design was chosen because the researcher did not randomize the subjects in full, but used classes that were already available at the school. The research involved two groups, namely the experimental class and the control class. The experimental class gained mathematical learning that was integrated with *computational thinking*, while the control class gained conventional learning.

Table 1. Research design

Group	Pretest	Treatment	Posttest
Experimental class	O ₁	Mathematics learning integrated with computational thinking	O ₂
Control class	O ₃	Conventional mathematics learning	O ₄

The population of this study is all grade VIII students at one of the State Junior High Schools in Central Jakarta. The research sample consists of two classes selected through purposive sampling techniques based on considerations of the equality of students' initial abilities, the recommendations of the mathematics teacher, and the similarity of the material studied. One class was designated as an experimental class with a total of 32 students, while another class was designated as a control class with a total of 32 students. Thus, the total number of research samples is 64 students.

The research was carried out through three main stages, namely the preparation stage, the implementation stage, and the data collection stage. In the preparation stage, the researcher compiled learning tools, student worksheets, mathematical reasoning ability test instruments, student response questionnaires, and observation sheets. The learning tools in the experimental class are designed by integrating five *components of computational thinking*, namely decomposition, pattern recognition, abstraction, algorithmic thinking, and evaluation.

At the implementation stage, the experimental class followed mathematics learning with *computational thinking-based* activities. The teacher begins the learning by giving a contextual problem, then students are directed to break the problem into small parts, identify patterns, determine important information, develop a solution strategy, and evaluate the correctness of the answers. Meanwhile, the control class obtained conventional learning through teacher explanations, giving sample questions, limited discussions, and practice questions.

The main instrument in this study is the mathematical reasoning ability test in the form of descriptions. Indicators of mathematical reasoning ability used include: (1) the ability to propose mathematical conjectures, (2) the ability to formulate evidence or reasons for a statement, (3) the ability to draw logical conclusions, and (4) the ability to check the truth of an argument or procedure. In addition to the test, this study also uses questionnaires to find out students' responses to learning and observation sheets to see the implementation of learning.

Data were analyzed using descriptive and inferential statistics. Descriptive statistics are used to obtain an overview of the average value, standard deviation, minimum value, and maximum value. The quality of the instrument was analyzed through tests of content validity, empirical validity, reliability, difficulty, and differentiating power. The analysis prerequisite test includes the Shapiro-Wilk normality test and the Levene's Test homogeneity. Furthermore, the paired samples t-test was used to analyze the improvement in mathematical reasoning ability in each class, while the independent samples t-test was used to test the differences in initial, posttest, and N-Gain ability between the experimental class and the control class. The effect size analysis used Cohen's d, while ANCOVA was used to test for differences in students' final ability after pretest scores were controlled as covariates.

RESULT AND DISCUSSION

RESULT

This study aims to determine the influence of the integration of *computational thinking* in mathematics learning on students' mathematical reasoning skills. The analysis was carried out on 64 students divided into 32 students in the experimental class and 32 students in the control class. The results of the research were presented in stages, including instrument quality analysis, descriptive statistics, prerequisite tests, improvement tests, difference tests, *N-Gain*, *effect size*, ANCOVA, student responses, and observation of learning implementation.

Table 2. Descriptive statistics of students' mathematical reasoning ability

Group	N	Pretest Mean	SD	Posttest Mean	SD	Mean N-Gain	Category
Experimental	32	52.06	6.59	82.28	8.76	0.645	Medium
Control	32	50.25	5.94	68.56	7.60	0.373	Medium

Source: Researcher

Based on Table 2, the average *pretest* of the experimental class was 52.06, while the control class was 50.25. This score shows that the initial ability of students in both classes is relatively close. After the treatment was administered, the average *posttest*

of the experimental class increased to 82.28, while the control class increased to 68.56. The average *N-Gain* of the experimental class was 0.645 and was in the medium category, while the control class obtained an average *N-Gain* of 0.373 and was also in the medium category. Although both classes improved, the achievement of the experimental class was higher than that of the control class.

Table 3. Content validity of mathematical reasoning test

Aspect	Aiken's V	Category
Relevance to mathematical reasoning indicators	0.91	Very valid
Accuracy of mathematical content	0.88	Very valid
Clarity of item construction	0.86	Very valid
Language appropriateness	0.84	Valid
Scoring rubric suitability	0.89	Very valid

Source: Researcher

The validity of the content is carried out through an expert assessment of the suitability of the question with the indicator of mathematical reasoning ability. The results in Table 3 show that *Aiken's V value* is in the range of 0.84 to 0.91. Thus, the test instrument is declared valid in terms of content and suitable for use after minor improvements are made based on the validator's suggestions.

Table 4. Empirical validity of test items

Item	r-count	Sig.	Decision
Item 1	0.671	< .001	Valid
Item 2	0.728	< .001	Valid
Item 3	0.694	< .001	Valid
Item 4	0.752	< .001	Valid
Item 5	0.705	< .001	Valid

Source: Researcher

The empirical validity test was carried out by correlating the score of each question item with the total score. Based on Table 4, all question items obtained a

significance value of less than 0.05. This means that the five question items are valid and can be used to measure students' mathematical reasoning skills.

Table 5. Reliability of mathematical reasoning test

Component	Coefficient	Category
5	0.842	High reliability
Inter-rater reliability/ICC	0.887	Very good agreement

Source: Researcher

The reliability of the instrument was tested using *Cronbach's Alpha* because the instrument was in the form of a description question. *Cronbach's Alpha* value of 0.842 indicates that the instrument has a high internal consistency. In addition, the *inter-rater reliability* value of 0.887 indicates excellent assessment suitability between the first and second assessors.

Table 6. Item difficulty index

Item	Difficulty Index	Category
Item 1	0.68	Medium
Item 2	0.61	Medium
Item 3	0.54	Medium
Item 4	0.49	Medium
Item 5	0.43	Medium

Source: Researcher

The results of the difficulty level test in Table 6 show that all question items are in the medium category. This condition shows that the questions are not too easy and not too difficult, so it is appropriate to measure students' mathematical reasoning abilities in the research sample.

Table 7. Item discrimination index

Item	Discrimination Index	Category
Item 1	0.42	Good
Item 2	0.46	Good
Item 3	0.39	Fair

Item	Discrimination Index	Category
Item 4	0.51	Good
Item 5	0.37	Fair

Source: Researcher

Based on Table 7, three question items have good distinguishing power and two question items have sufficient distinguishing power. Thus, all question items can be used because they are able to distinguish students with high and low mathematical reasoning skills.

Table 8. Tests of normality

Data	Group	Shapiro-Wilk Statistic	df	Sig.	Decision
Pretest	Experimental	0.967	32	0.431	Normal
Posttest	Experimental	0.960	32	0.277	Normal
N-Gain	Experimental	0.973	32	0.578	Normal
Pretest	Control	0.962	32	0.310	Normal
Posttest	Control	0.980	32	0.789	Normal
N-Gain	Control	0.960	32	0.281	Normal

Source: Researcher

The normality test was performed using *Shapiro-Wilk* because the number of samples in each class was less than 50. The results in Table 8 show that the overall significance value is greater than 0.05. Thus, *the pretest, posttest, and N-Gain data* in the experimental class and the control class were normally distributed.

Table 9. Test of homogeneity

Data	Levene Statistic	df1	df2	Sig.	Decision
Pretest	0.017	1	62	0.897	Homogeneous
Posttest	1.556	1	62	0.217	Homogeneous
N-Gain	3.323	1	62	0.073	Homogeneous

Source: Researcher

The homogeneity test was carried out using *Levene's Test*. Table 9 shows that the significance values of *the pretest, posttest, and N-Gain* are greater than 0.05. This

means that the variance of data between the experimental class and the control class is homogeneous, so the analysis can be continued using parametric tests.

Table 10. Equivalence test of students' initial mathematical reasoning ability

Group	N	Pretest Mean	SD
Experimental	32	52.06	6.59
Control	32	50.25	5.94

Source: Researcher

Table 11. Independent samples t-test of pretest scores

Group Comparison	t	df	Sig. (2-tailed)	Mean Difference	Decision
Experimental-Control	1.156	62	0.252	1.81	Not significant

Source: Researcher

The initial ability equivalence test was carried out with an independent samples t-test against the pretest score. Based on Table 11, the significance value of 0.252 is greater than 0.05. Thus, there was no significant difference in initial ability between the experimental class and the control class. Both classes can be considered to have equal initial abilities before treatment is given.

Table 12. Paired samples t-test of experimental class

Data	Mean	SD/Result
Pretest	52.06	6.59
Posttest	82.28	8.76
Paired difference	30.22	4.90
t-test result	t = 34.906	df = 31; Sig. < .001

Source: Researcher

The results of the paired samples t-test in the experimental class showed a significance value of less than 0.001. Thus, there is a significant improvement in mathematical reasoning skills after students participate in mathematics learning integrated with *computational thinking*.

Table 13. Paired samples t-test of control class

Data	Mean	SD/Result
Pretest	50.25	5.94
Posttest	68.56	7.60
Paired difference	18.31	5.08
t-test result	t = 20.381	df = 31; Sig. < .001

Source: Researcher

The results of the paired samples t-test in the control class also showed a significant improvement in mathematical reasoning ability. However, the average increase in the control class of 18.31 was lower than the average increase in the experimental class of 30.22. This difference shows that conventional learning still provides improvements, but not as strong as learning that integrates *computational thinking*.

Table 14. Independent samples t-test of posttest scores

Group	N	Posttest Mean	SD
Experimental	32	82.28	8.76
Control	32	68.56	7.60

Group Comparison	t	df	Sig. (2-tailed)	Mean Difference	Decision
Experimental-Control	6.693	62	< .001	13.72	Significant

Source: Researcher

The results of independent samples t-test on *posttest scores* showed a significance value of less than 0.001. Thus, there was a significant difference in final mathematical reasoning ability between the experimental class and the control class. The average *posttest* of the experimental class was higher than that of the control class, so the integration of *computational thinking* provided better learning outcomes than conventional learning.

Table 15. N-Gain analysis

Group	N	Mean N-Gain	SD	Category
Experimental	32	0.645	0.149	Medium
Control	32	0.373	0.111	Medium

Source: Researcher

N-Gain *analysis* is used to determine the improvement of students' mathematical reasoning abilities by considering the initial score and the maximum score. The average N-Gain of the experimental class was 0.645, while the control class was 0.373. Both values were in the medium category, but the increase in the experimental class was higher than the control class.

Table 16. Independent samples t-test of N-Gain scores

Group Comparison	t	df	Sig. (2-tailed)	Mean Difference	Decision
Experimental-Control	8.293	62	< .001	0.272	Significant

Source: Researcher

The results of independent samples t-test on N-Gain showed a significance value of less than 0.001. Thus, there was a significant difference in the improvement of mathematical reasoning skills between the experimental class and the control class. These results support that the integration of *computational thinking* in mathematics learning is more effective than conventional learning.

Table 17. Effect size analysis

Comparison		Cohen's d	Category
Posttest control	experimental-	1.673	Large
N-Gain control	experimental-	2.073	Very large

Source: Researcher

Effect size *analysis* showed that Cohen's d value at the posttest comparison was 1.673 and at the N-Gain comparison was 2.073. These values are in the large to very large category. This means that the integration of *computational thinking* not only results in a statistically significant difference, but also has a strong practical impact on improving students' mathematical reasoning abilities.

Table 18. Homogeneity of regression slopes

Source	F	Sig.	Decision
Pretest × Group	0.554	0.460	Fulfilled

Source: Researcher

Table 19. ANCOVA results

Source	Sum Squares	of df	F	Sig.	Partial Squared	Eta
Group	2194.540	1	86.882	< .001	0.588	
Pretest	2627.553	1	104.025	< .001	0.630	
Error	1540.791	61	-	-	-	

Source: Researcher

Table 20. Adjusted means based on ANCOVA

Group	Adjusted Mean
Experimental	81.34
Control	69.50

Source: Researcher

Prior to ANCOVA, the assumption of regression slope homogeneity was tested through *pretest* and group interactions. A significance value of 0.460 indicates that the assumption is met. *The results of ANCOVA* in Table 19 show that the learning group had a significant effect on the *posttest* of mathematical reasoning ability after the *pretest* score was controlled, with a value of $F = 86.882$ and $p < 0.001$. A *partial eta squared* value of 0.588 indicates that 58.8% variation in final mathematical reasoning ability can be explained by differences in learning models after considering students' initial abilities. The average corrected for the experimental class was 81.34, higher than the control class of 69.50.

Table 21. Students' responses toward computational thinking-based mathematics learning

Aspect	Mean Score	Category
Ease of understanding learning steps	3.58	Very high
Active involvement in problem solving	3.64	Very high
Ability to identify problem patterns	3.52	Very high

Aspect	Mean Score	Category
Helpfulness in arranging solution steps	3.69	Very high
Encouragement to explain mathematical reasons	3.61	Very high
Interest in mathematics learning	3.56	Very high

Source: Researcher

The results of the questionnaire showed that students responded very positively to computational thinking-based mathematics learning. The highest score was found in the aspect of assistance in compiling completion steps, which was 3.69. These findings show that students feel that the learning stages based on decomposition, pattern recognition, abstraction, algorithmic thinking, and evaluation help them understand problems and structure mathematical arguments more coherently.

Table 22. Observation of learning implementation

Observed Aspect	Implementation Percentage	Category
Opening and orientation of contextual problem	91.25	Very good
Decomposition activity	88.75	Good
Pattern recognition activity	87.50	Good
Abstraction activity	86.25	Good
Algorithmic thinking activity	90.00	Very good
Evaluation and reflection activity	88.75	Good

Source: Researcher

The results of the observation showed that the learning in the experimental class was carried out well. Teachers are able to direct students to understand problems, break down information, find patterns, filter important information, formulate solution steps, and evaluate answers. Good learning implementation supports the validity of the treatment process because the integration of *computational thinking* is really applied in learning activities.

Overall, test results, *N-Gain*, *effect size*, *ANCOVA*, questionnaire, and observation showed a consistent pattern of findings. The integration of *computational thinking* in

mathematics learning makes a positive contribution to improving students' mathematical reasoning skills. This finding can be explained because the computational *thinking stage* encourages students to not only follow the procedure, but also understand the structure of the problem, develop a solution strategy, provide logical reasons, and re-examine the correctness of the answers. Thus, computational thinking-based mathematics learning can be understood as a relevant pedagogical approach to developing mathematical reasoning in the context of 21st century learning.

The results of this study are in line with the study of Ye et al. (2023) which shows that the integration of *computational thinking* in K–12 mathematics learning supports improving the quality of learning and developing students' thinking processes. These findings are also in line with Chan et al. (2023) who affirm that various *computational thinking-based* approaches have been used in mathematics learning to strengthen problem-solving and systematic thinking. In addition, Lehmann (2025) show a relationship between mathematical thinking and computational thinking in solving mathematical problems. Therefore, the integration of *computational thinking* can be an alternative learning strategy that not only emphasizes the final outcome, but also the quality of the student's reasoning process.

DISCUSSION

This study was conducted to examine whether the integration of computational thinking in mathematics learning could improve students' mathematical reasoning skills. The findings indicate that students who participated in computational thinking-based mathematics learning achieved significantly better mathematical reasoning performance than students who experienced conventional instruction. This result directly answers the research objective and confirms that computational thinking contributes positively to the development of mathematical reasoning. Although both groups showed improvement, the experimental group demonstrated higher posttest achievement, greater learning gain, and stronger practical impact. These findings suggest that the improvement was not solely caused by regular instructional exposure, but also by the structured reasoning process embedded in computational thinking activities.

The findings can be scientifically interpreted through the cognitive dimensions of computational thinking itself. Computational thinking encourages students to decompose complex problems, identify mathematical patterns, abstract essential information, formulate algorithmic procedures, and evaluate the correctness of solutions. In mathematics learning, these processes are highly relevant to reasoning activities because mathematical reasoning requires students to analyze relationships, construct arguments, justify procedures, and verify conclusions logically. Recent studies have emphasized that computational thinking is increasingly recognized as a core competency in mathematics education because it supports logical reasoning and

systematic problem solving. Chytas et al. (2024) explained that computational thinking integration in mathematics learning across various countries consistently strengthens higher-order thinking skills and mathematical problem solving. Similarly, Ghifari et al. (2024) stated that computational thinking in mathematics learning improves logical reasoning and students' ability to solve mathematical problems systematically.

The present findings also support the argument that computational thinking is not limited to computer programming activities but functions as a structured way of thinking applicable to mathematics learning. Rich et al. (2024) argued that computational thinking enables students to formulate detailed mathematical solutions through decomposition, abstraction, and algorithmic reasoning. In the current study, students in the experimental class were guided through learning stages involving decomposition, pattern recognition, abstraction, algorithmic thinking, and evaluation. These stages appear to help students organize mathematical information more coherently and develop stronger reasoning structures when solving problems. This explains why students in the experimental class were able not only to produce answers but also to provide clearer mathematical justification.

The findings are also consistent with recent international studies emphasizing the close relationship between computational thinking and mathematical reasoning processes. Nordby et al. (2022) found that students' computational thinking ability influences how they identify relevant mathematical information, select strategies, and construct solutions in solving Pythagorean theorem problems. Likewise, Muhammad et al. (2024) reported that decomposition, abstraction, pattern recognition, and algorithmic design significantly influence mathematical problem-solving performance in secondary education. These studies support the present findings because students who engaged in computational thinking activities tended to approach mathematical problems more analytically and systematically than students who relied mainly on procedural instruction.

Another important interpretation concerns the role of computational thinking as a pedagogical scaffold for reasoning development. The observation and questionnaire results in this study showed that students perceived computational thinking stages as helpful in organizing solution steps and explaining mathematical reasons. This finding is important because mathematical reasoning is not merely the ability to obtain correct answers, but also the ability to justify and communicate logical thinking. Recent literature reviews by Kafai & Proctor (2022) concluded that computational thinking-based learning positively affects higher-order thinking skills, logical reasoning, and problem-solving ability because it encourages students to think systematically and reflectively. Similarly, Dobgenski et al. (2025) explained that computational thinking integration in mathematics education supports reflective and contextual learning processes that strengthen students' reasoning and analytical skills.

However, the findings should be interpreted proportionally because the control group also showed significant improvement. This means that conventional mathematics learning still contributed positively to students' mathematical reasoning development. Therefore, the findings do not imply that conventional learning is ineffective. Rather, computational thinking-based learning appears to provide stronger additional value by making reasoning processes more explicit, structured, and reflective. This distinction is important academically because the effectiveness of computational thinking lies not in replacing mathematical instruction, but in enriching mathematics learning with systematic cognitive processes that support reasoning development.

The novelty of this study lies in the positioning of computational thinking as an instructional framework specifically aimed at improving mathematical reasoning ability. Many recent studies have focused primarily on computational thinking skills, programming integration, or problem-solving outcomes. For instance, Ersozlu et al. (2023) emphasized the integration of computational thinking in mathematics classrooms from a systematic review perspective, while Wang et al. (2022) examined computational thinking as a predictor of creative mathematical thinking. In contrast, the present study specifically demonstrates empirically that computational thinking integration significantly improves mathematical reasoning ability through evidence from posttest analysis, N-Gain, effect size, ANCOVA, student responses, and classroom observations. This comprehensive evidence strengthens the contribution of the study because the effectiveness of computational thinking is supported statistically, cognitively, and pedagogically.

The practical implication of this study is that mathematics teachers can integrate computational thinking stages into classroom activities to strengthen students' reasoning processes. Teachers may design learning tasks that require students to identify problem structures, recognize patterns, formulate logical procedures, evaluate answers, and explain mathematical arguments. Such learning is highly relevant to 21st-century education because it encourages students to reason systematically and solve problems reflectively rather than relying solely on memorization. Furthermore, the findings suggest that computational thinking can be integrated into mathematics learning without transforming mathematics into computer science instruction. Instead, computational thinking functions as a thinking framework that supports deeper mathematical understanding and reasoning quality.

Future studies should involve broader samples, different educational levels, and various mathematical topics to examine the consistency of these findings across contexts. Further research is also needed to investigate which component of computational thinking contributes most strongly to mathematical reasoning development. For example, future researchers may analyze whether abstraction, decomposition, algorithmic thinking, or evaluation has the greatest influence on

students' reasoning performance. In addition, qualitative approaches such as interviews, think-aloud protocols, and analysis of students' written reasoning can provide deeper insight into how computational thinking shapes mathematical reasoning processes during learning activities.

CONCLUSION

This study shows that applying *computational thinking* in mathematics learning can help improve students' mathematical reasoning skills. Through this approach, students are guided to understand problems more clearly, identify patterns, focus on important information, arrange solution steps, and review their answers. In this way, students do not only try to find the final answer, but also learn to explain the reasons behind each step in a more organized manner.

The findings suggest that *computational thinking* can be used as a useful learning approach in mathematics. It helps students think more systematically and prevents them from solving problems too quickly without proper reasoning. For teachers, this approach can be an alternative strategy to design more active and meaningful mathematics lessons, especially when students are required to solve problems that involve reasoning. The positive student responses and the smooth implementation of the learning activities also indicate that this approach can be applied well in the classroom.

However, this study still has some limitations. The research was conducted only in two classes at one school, so the results may not fully represent different schools, grade levels, or student characteristics. In addition, the research was carried out within a relatively short period, so it has not yet shown the long-term effects of *computational thinking* on students' learning. Future studies are suggested to involve larger samples, different educational levels, and more varied mathematics topics. Further research may also examine the effect of *computational thinking* on other mathematical abilities, such as problem-solving, mathematical communication, numeracy literacy, and mathematical creativity.

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