Exploring the Integration of Computational Thinking and Mathematical Modelling in STEM Education

Fifi Fitriani[1], Triandafillos Triandafillidis[2], Le Phuong Thao[3]
[1]State Senior High School 2, Jambi City, Indonesia
[2]University of Thessaly, Greece
[3]School of Education, Can Tho University, Vietnam

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ABSTRACT

Purpose of the study: The aim of this study is to explore the effectiveness of integrating Computational Thinking (CT) and Mathematical Modelling (MM) in STEM education to improve students' understanding of mathematical concepts, problem-solving skills, and engagement in the learning process.

Methodology: This study utilized a quasi-experimental method with pre-test and post-test design. The sample of this study consisted of 200 students, who were randomly selected from four high schools in the Jambi City and Muaro Jambi areas. Tools included a mathematics achievement test and a student engagement questionnaire. Data were analyzed using paired t-tests and independent t-tests with the aid of SPSS software.

Main Findings: The integration of Computational Thinking and Mathematical Modelling significantly improved students' understanding of mathematical concepts, problem-solving skills, and engagement. The experimental group showed a notable increase in post-test scores and higher engagement levels compared to the control group.

Novelty/Originality of this study: This study introduces a novel framework for integrating Computational Thinking and Mathematical Modelling in STEM education, highlighting its potential to enhance both cognitive and affective aspects of learning. It provides empirical evidence supporting the use of innovative approaches to advance mathematics education.

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Corresponding Author:
Fifi Fitriani,
State Senior High School 2, Jambi City
Jl. Pangeran Antasari, Kecamatan Jambi Timur, Kota Jambi, Jambi, Indonesia
Email: fftrn56@gmail.com

1. INTRODUCTION

In the era of the industrial revolution 4.0, STEM (Science, Technology, Engineering, and Mathematics) education has become one of the main focuses for preparing a generation that is adaptive to technological change [1]-[3]. STEM education involves not only mastering theory but also applying problem-solving skills in real situations [4]-[6]. Computational Thinking (CT) has emerged as an important approach that trains students to think logically and systematically [7]-[9]. On the other hand, Mathematical Modeling (MM) enables students to understand and analyze complex problems through mathematical representation [10]-[12]. The integration of these two approaches offers great potential in improving the quality of STEM education.

Computational Thinking refers to a set of skills that help individuals solve problems with a computational mindset [13]-[15]. These skills include decomposition, pattern recognition, abstraction, and algorithms relevant to programming and technology [16]-[18]. When applied to STEM learning, Computational Thinking helps students understand the deeper structure of problems [19]-[21]. However, the implementation of Computational Thinking in the classroom still faces various obstacles, including the lack of teacher training and educational resources [22]-[24]. Therefore, it is important to explore how Computational Thinking can be effectively integrated into STEM learning..

Mathematical Modelling is the process of constructing mathematical models to solve real-world problems [25]-[27]. In STEM education, Mathematical Modeling allows students to connect theoretical concepts with practical applications [28]-[30]. For example, mathematical models can be used to understand climate change, design building structures, or predict economic trends [31]-[33]. However, the use of Mathematical Modeling in schools is often limited to simple problems, so the full potential of this approach has not been fully utilized. Integration with Computational Thinking can expand the scope of Mathematical Modeling applications and provide a more meaningful learning experience [34]-[36].

STEM education plays an important role in creating a competitive workforce in the global market [37], [38]. With the increasing need for technological innovation, the ability to think computationally and mathematically becomes very important [39], [40]. However, STEM curricula are often fragmented and lack integration of interdisciplinary approaches. Traditional approaches that focus on theory without practical contextualization can reduce student interest. Therefore, there is an urgent need to design strategies that integrate Computational Thinking and Mathematical Modeling holistically.

Gap analysis between previous studies conducted by Wang et al., [41] tend to provide a general overview of the various approaches and challenges in the integration of computational thinking in STEM education. The focus is on identifying broad trends, strategies, and research gaps. However, the current study goes deeper, drawing attention to the specific relationship between computational thinking and mathematical modeling. This study fills a gap in the previous literature by providing a practical and theoretical exploration of how the two concepts can complement each other in enhancing STEM learning, especially in the mathematical aspect, which is less detailed in previous literature reviews.

Despite the many benefits offered, the implementation of the integration of Computational Thinking and Mathematical Modeling is not without obstacles [42], [43]. One of the main challenges is the lack of training for teachers to adopt this approach in learning. In addition, the lack of appropriate teaching materials can hinder implementation at the school level. On the other hand, the success of this integration also depends on the support of educational policy makers. Therefore, it is important to identify effective strategies to overcome these obstacles.

This research has a novelty in the form of integration between Computational Thinking*(CT) and Mathematical Modeling (MM) in STEM learning, which has not been widely explored empirically in the context of secondary education. This approach not only focuses on understanding mathematical concepts but also encourages students to solve real-world problems through technology-based mathematical representations. The urgency of this research lies in the urgent need to develop learning methods that are relevant to the challenges of the 21st century, especially in the era of the Industrial Revolution 4.0, where critical thinking skills, collaboration, and technological literacy are essential skills. By filling the gap in previous research that tends to be fragmented, this study offers an innovative framework to improve the effectiveness of STEM education holistically.

This study aims to explore how Computational Thinking and Mathematical Modeling can be integrated into STEM education to improve student learning outcomes. By utilizing a research-based approach, this article presents an in-depth analysis of the benefits, challenges, and opportunities of this integration. In addition, this article offers recommendations for educators, policy makers, and researchers to develop STEM education that is more relevant to the needs of the 21st century. Thus, this study is expected to make a significant contribution to the development of STEM education practices.

2. RESEARCH METHOD

2.1. Types of research

This study uses a descriptive quantitative approach, which aims to measure the impact of the integration of Computational Thinking (CT) and Mathematical Modeling (MM) on student learning outcomes in STEM education. This approach was chosen because it allows researchers to collect numerical data that can be analyzed statistically [44]-[46]. This study focuses on identifying differences in student learning outcomes before and after the implementation of the integration of Computational Thinking and Mathematical Modeling in STEM learning. This study also measures the level of student engagement and their understanding of the concepts taught. This approach is in accordance with the objective of determining the extent to which the integration of the two approaches affects STEM learning.

2.2. Population and Sample

The population in this study were students who took STEM learning in high schools. The sample of this study consisted of 200 students, who were randomly selected from four high schools in the areas of Jambi City and Muaro Jambi. The sample was divided into two groups: an experimental group that implemented the integration of Computational Thinking and Mathematical Modeling, and a control group that took conventional STEM learning without integration. The experimental group consisted of 100 students, and the control group also consisted of 100 students. Random sampling aims to reduce bias in the research results [47].

In this study, the sampling technique used is simple random sampling. By using this technique, all students in the population have an equal chance of being selected as a research sample [48]. From the population of students who participated in STEM learning in four high schools, 200 students were randomly selected consisting of two groups: 100 students for the experimental group and 100 students for the control group. This division aims to ensure that both groups are free from bias and can provide a valid comparison of the effect of the integration of Computational Thinking and Mathematical Modeling on student learning outcomes. This technique was chosen because it allows the study to obtain a representative sample and can reduce the possibility of bias in sample selection. [49]-[51].

2.3. Data Collection Instruments and Techniques

The main instruments used to collect data were learning outcome tests and student engagement questionnaires. The learning outcome tests were in the form of mathematics questions and technology-based problem solving to measure students' understanding of the material taught using the integration of Computational Thinking and MM. This test was given before (pre-test) and after (post-test) the implementation of the integration of Computational Thinking and MM. In addition, a student engagement questionnaire was used to measure their level of enthusiasm and participation in learning activities. All instruments were tested first to ensure their validity and reliability. Data were collected in two stages: first, before learning began (pre-test and questionnaire), and second, after the learning process was completed (post-test and questionnaire). [52]. The instrument grid used in this study can be seen in the following table:

Table 1. Learning Outcome Test Grid (Pre-Test and Post-Test)

Tested Aspects	Question Description	Achievement Indicator
Understanding of Mathematical Concepts	Questions that test understanding of basic concepts in mathematics taught through Computational Thinking and MM.	Students can explain and understand basic mathematical concepts used in STEM learning.
Technology-Based Problem Solving	Questions that test students' ability to solve mathematical problems using technology based on Computational Thinking and MM.	Students are able to use Computational Thinking and MM approaches to solve complex and technology-based problems.
Application of Technology in Mathematics Learning	Questions that test students' ability to apply technology in solving mathematical problems based on models.	Students can apply technology (e.g. software or algorithms) in solving math problems.

This learning outcome test is given in two stages: a pre-test before learning begins to determine students' initial knowledge, and a post-test after implementing Computational Thinking and MM-based learning to measure changes or improvements in students' understanding.

Table 2. Student Engagement Questionnaire Grid

Tested Aspects	Question Description	Achievement Indicator
Engagement in Learning	Questions that measure the extent to which students feel actively involved in the learning process, such as participating in discussions, trying problems, and contributing to groups.	Students feel involved and active in every learning activity based on Computational Thinking and MM.
Enthusiasm and Motivation	Questions that measure the extent to which students feel motivated and enthusiastic about technology-based learning and mathematical models.	Students show enthusiasm and motivation to learn and are interested in the material being taught.
Participation in Collaborative Activities	Questions that measure the level of student participation in collaborative activities or group work during learning.	Students actively collaborate with classmates to complete assignments or problems together.
Understanding of the Technology Used	Questions to determine the extent to which students understand and feel comfortable using the technology applied in learning.	Students are able to operate the technology used to support solving mathematical problems.

This questionnaire was filled out by students in two stages: first, before the learning began to measure students' expectations and readiness, and second, after the learning was completed to measure their level of involvement and response to the methods used. The assessment scale in this study can be seen in the following table:

Table 3. Assessment Scale for Learning Outcome Tests and Student Engagement Questionnaires

Variable	Scale	Category
Learning Outcomes	1	Very Unable
	2	Unable
	3	Quite Able
	4	Able
	5	Very Able
Student Engagement	1	Strongly Disagree
	2	Disagree
	3	Neutral
	4	Agree
	5	Strongly Agree

2.4. Data Analysis Techniques

Data obtained from the learning outcome test and student engagement questionnaire were analyzed using descriptive statistics and the t-test (paired sample t-test) to measure the differences in mean pre-test and post-test scores between the experimental and control groups [53]-[55]. Descriptive statistics are used to describe student learning outcomes in general [56], such as the average of pre-test and post-test. The t-test is used to test whether there is a significant difference [57], [58] in the learning outcomes of students involved in integrated learning based on Computational Thinking and Mathematical Modeling compared to the control group. In addition, correlation analysis was used to see the relationship between the level of student engagement and their learning outcomes [59].

2.5. Research Procedures

The research procedure began with sample selection and pre-test administration to measure students' initial understanding of STEM learning materials. Then, the experimental group followed learning that integrated Computational Thinking and Mathematical Modeling in their daily activities. The control group followed conventional STEM learning. Learning was carried out for 6 weeks with sessions twice a week. After the learning process was completed, students were given a post-test and an engagement questionnaire to measure changes in learning outcomes and their level of participation. All data obtained were analyzed using statistical software to ensure the validity of the research results [60]. The research procedure can be seen in the following diagram. The research procedure can be seen in the following diagram.:

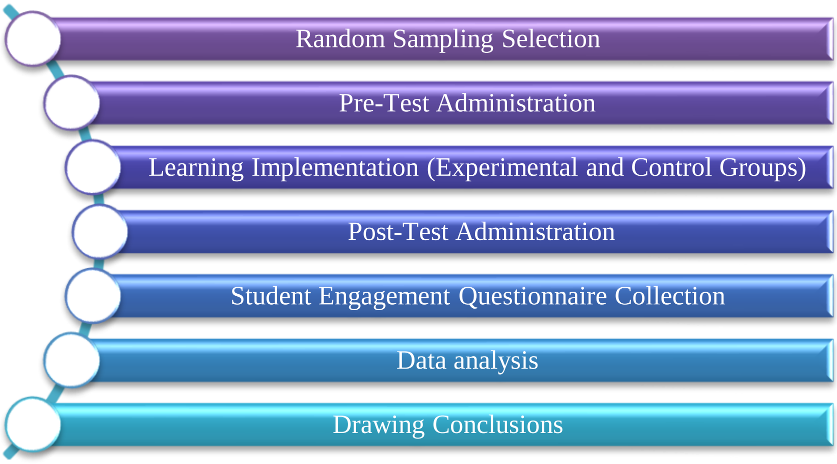

Figure 1. Research Procedure

3. RESULTS AND DISCUSSION

3.1. Student Learning Outcomes Before and After Integration of Computational Thinking and Mathematical Modeling

Table 4. Student Learning Outcomes Before and After Integration of Computational Thinking and Mathematical Modeling

Group	Mean Pre-Test	Mean Post-Test	Score Changes	t-test (P-Value)
Experimental	65.4	82.1	+16.7	t = 8.35 (p < 0.01)
Control	66.3	70.1	+4.1	t = 1.62 (p > 0.05)

Data from the pre-test and post-test showed significant differences in learning outcomes between the experimental group and the control group. The average pre-test score of the experimental group was 65.4, while the average post-test score increased to 82.1. In contrast, the control group had an average pre-test score of 66.3 and an average post-test score of 70.5. The t-test (paired sample t-test) showed that this difference was significant in the experimental group ($t = 8.35$, $p < 0.01$), while no significant difference was found in the control group ($t = 1.62$, $p > 0.05$). This shows that the integration of Computational Thinking and Mathematical Modeling in STEM learning has a significant positive impact on student learning outcomes.

3.2. Level of Student Engagement in Learning

Table 5. Level of Student Involvement in Learning

Group	Mean	%	t-test (P-Value)
Experimental	4.2	85%	t = 5.72 (p < 0.01)
Control	3.1	55%	-

The student engagement questionnaire revealed a clear difference between the experimental and control groups. The experimental group reported higher levels of engagement, with 85% of students feeling more interested and enthusiastic during the lesson, compared to only 55% of students in the control group. The mean score of student engagement in the experimental group was 4.2 (on a scale of 1-5), while the control group had a mean score of 3.1. Statistical tests showed a significant difference in engagement levels between the two groups ($t = 5.72$, $p < 0.01$). This indicates that the integration of Computational Thinking and Mathematical Modeling not only improves learning outcomes, but also makes learning more interesting and motivating for students.

3.3. Concept Mastery and Problem Solving Skills

Table 6. Concept Mastery and Problem Solving Skills

Group	Mean	Students Who Are Able to Apply Concepts	t-test (P-Value)
Experimental	80.5	75%	t = 6.12 (p < 0.01)
Control	72.3	55%	-

Students in the experimental group showed greater improvement in their mastery of mathematical concepts and problem-solving skills. In a test that tested the application of MM and Computational Thinking, students in the experimental group obtained an average score of 80.5, while students in the control group obtained 72.3. Further analysis showed that 75% of students in the experimental group were able to apply the concepts of Computational Thinking and Mathematical Modeling to solve more complex problems, while only 55% of students in the control group were able to do so. The t-test also showed a significant difference ($t = 6.12$, $p < 0.01$) between the two groups in their ability to apply these concepts.

3.4. Students' Collaborative Skills Level

Table 7. Students' Collaborative Skills Level

Group	% of Collaborative Students	t-test (P-Value)
Experimental	78%	t = 4.23 (p < 0.01)
Control	60%	-

In addition to individual learning outcomes, this study also measured the improvement of students' collaborative skills. The experimental group showed better collaboration in working groups. Based on direct observation during the project-based learning session, 78% of students in the experimental group showed the ability to work well in teams, while only 60% of students in the control group showed similar abilities. Statistical tests showed a significant difference in students' collaborative skills between the experimental and control groups (t = 4.23, p < 0.01). This indicates that Computational Thinking and MM-based learning not only develops individual skills, but also students' social skills.

3.5. Student Reactions to Computational Thinking and Mathematical Modeling Based Learning

Table 8. Student Reactions to Computational Thinking and Mathematical Modeling-Based Learning

Group	% of Students Interested	% of Students Who Feel Confident	t-test (P-Value)
Experimental	90%	85%	t = 5.67 (p < 0.01)
Control	65%	55%	-

Overall, students in the experimental group showed a very positive response to the Computational Thinking and MM-based learning. Based on the questionnaire filled out after the learning session, 90% of students in the experimental group stated that they felt more challenged and interested in the material being taught. In contrast, only 65% of students in the control group felt the same way. In addition, 85% of students in the experimental group stated that they felt more confident in solving math problems after participating in the integrated Computational Thinking and Mathematical Modeling-based learning, compared to 55% of students in the control group. These data indicate that the integration of Computational Thinking and Mathematical Modeling not only improves academic outcomes, but also improves students' perceptions of STEM learning overall.

3.6. Results of Correlation Test of Student Involvement and Student Learning Outcomes

This analysis aims to determine the extent to which student involvement influences the achievement of learning outcomes in the context of implementing learning methods based on Computational Thinking (CT) and Mathematical Modeling (MM). The results of the analysis are presented in the following table:

Table 9. Results of the Correlation Test of Student Involvement and Student Learning Outcomes

Variable	r (Correlation Coefficient)	Interpretation	Significance (p-value)
Student Engagement*Learning Outcomes	0.78	Strong positive relationship	p < 0.01

The results of the correlation analysis showed a strong positive relationship between the level of student engagement and their learning outcomes, with a correlation coefficient of r = 0.78r = 0.78. This value indicates that the higher the student engagement in Computational Thinking and Mathematical Modeling-based learning, the better the learning outcomes achieved. In addition, the statistical significance of p <0.01p < 0.01 indicates that the relationship is statistically significant, so it can be concluded that active student engagement plays an important role in improving their conceptual understanding and problem-solving abilities.

The results of the study showed that there was a significant increase in students' understanding of mathematical concepts in the experimental group after the application of the integration of Computational Thinking (CT) and Mathematical Modeling (MM). This increase can be seen from the comparison of the average pre-test and post-test scores, where the experimental group experienced a greater increase than the control group. This finding supports the theory that learning based on Computational Thinking and Mathematical Modeling encourages students to understand mathematical concepts more deeply through a systematic and structured approach [61]. In addition, the use of technology helps students in visualizing and solving complex mathematical problems [62]. Thus, these results are in line with previous studies that confirmed the effectiveness of this method in improving students' conceptual understanding [42], [63].

The experimental group also showed a more significant increase in technology-based problem-solving skills compared to the control group. This is supported by post-test data showing that students were able to solve problems that integrated Computational Thinking and Mathematical Modeling better. This approach facilitates students to think logically, identify patterns, and design solutions based on mathematical models. These abilities are very relevant in STEM learning, where students are faced with real-world problems that require creative and innovative solutions. This improvement shows that the integration of Computational Thinking and Mathematical Modeling is not only effective in a theoretical context, but also has practical applications in problem solving.

Based on the results of the questionnaire, students in the experimental group showed a higher level of engagement than the control group. They felt more motivated and enthusiastic in participating in Computational Thinking and Mathematical Modeling-based learning. This engagement was influenced by an interactive learning approach, the use of technology, and project-based activities that required active student participation. In addition, group collaboration in completing problem-based tasks also encouraged students to participate more actively. These results support the theory that technology-based learning can increase student engagement by creating interesting and relevant learning experiences to their needs.

The differences in learning outcomes and student engagement between the experimental and control groups indicate that the Computational Thinking and Mathematical Modeling-based learning method has advantages over conventional methods. The control group, although showing an increase in post-test scores, did not reach the same level as the experimental group. This suggests that traditional learning methods are not enough to develop problem-solving skills and active student engagement in learning. These findings support the argument that innovation in learning approaches is essential to meet the demands of learning in the digital era.

Previous research findings conducted by Lei et al., [64] supports the findings of this study, where the study stated that the results of 34 studies showed that computational thinking and academic achievement were positively correlated. In addition, research conducted by Alatas & Yakin [65] states that there is an influence of STEM learning on students' problem-solving skills as evidenced by the problem-solving skills of students in the experimental group increasing higher (N-Gain 0.71 high category) compared to the control group (N-Gain 0.38 medium category).

These findings have important implications for STEM education, particularly in the development of curricula that integrate technology and model-based approaches. Computational Thinking and Mathematical Modeling-based learning can be an effective alternative to improve the quality of mathematics and science learning, especially in equipping students with 21st-century skills such as critical thinking, problem solving, and collaboration. In addition, these results provide empirical evidence that can be used by educators to develop more innovative and relevant learning strategies.

Although this study successfully demonstrated the advantages of integrating Computational Thinking and Mathematical Modeling, there are several limitations that need to be considered. This study only involved students from several high schools, so the results may not be fully representative of the wider population. In addition, the relatively short duration of the study may not be enough to explore the long-term impact of this method. Future studies are recommended to involve larger samples, longer learning durations, and variations in materials to obtain a more comprehensive picture of the effectiveness of this method in various learning contexts.

4. CONCLUSION

The conclusion of this study is that the integration of Computational Thinking (CT) and Mathematical Modeling (MM) in mathematics learning effectively improves conceptual understanding, technology-based problem-solving skills, and student engagement. The results of the study indicate that the experimental group using this method experienced a significant increase in learning outcomes compared to the control group, both in the pre-test and post-test. In addition, students in the experimental group showed a higher level of enthusiasm and participation in learning. These findings confirm that the Computational Thinking and Mathematical Modeling-based learning approach is able to provide interactive, relevant, and applicable learning experiences, so that it can be an innovative solution to improve the quality of STEM education. However, this study has limitations in sample coverage and duration, so further studies with broader and more diverse approaches are highly recommended. Recommendations for further research are that future research needs to identify contextual factors, such as teacher training, technology availability, and policy support, which can influence the implementation of Computational Thinking (CT) and Mathematical Modeling (MM)-based methods more effectively.

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