

The application of the discovery learning model to students' computational thinking ability is reviewed from self-regulated learning

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Abstrak.

Computational thinking (CT) is a crucial skill for addressing the challenges of the 21st century. This study sought to investigate the impact of the Discovery Learning model on students' CT abilities, examining the influence of learning models, self-regulated learning (SRL) levels, and their interplay. The research employed a quantitative approach employing a quasi-experimental design involving two Grade 7 classes: an experimental group ($n = 26$) receiving instruction through the Discovery Learning model and a control group ($n = 24$) receiving conventional instruction. Instruments included an essay test assessing CT and a Likert-scale questionnaire evaluating SRL. Data were analyzed employing descriptive statistics, the Mann-Whitney test, and the Kruskal-Wallis test. The findings indicated that the average CT score in the experimental class (67.60) was superior to that in the control class (62.82). However, the Mann-Whitney test revealed that this disparity was not statistically significant ($p = 0.151 > 0.05$). Although no significant difference was observed when comparing the two learning models collectively, the Kruskal-Wallis test demonstrated a substantial effect of SRL on CT ($p = 0.000$). Furthermore, a significant interaction was identified between the learning model and the SRL level ($p = 0.000$). Notably, students with high SRL achieved the highest CT performance within the Discovery Learning group. These findings underscore the efficacy of combining the Discovery Learning model with high levels of student self-directed learning in enhancing computational thinking abilities. This evidence suggests that integrating teaching models with student learning autonomy yields more favorable outcomes.

Kata kunci:

Computational thinking; discovery learning; self-regulated learning

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INTRODUCTION

Computational thinking (CT) is a crucial skill that students must acquire to navigate the challenges of the 21st century. Shute et al. (2017) define CT as the conceptual framework essential for solving problems with or without computers, ensuring that the solutions are reusable in various contexts. Within the context of mathematics education, CT encompasses the abilities of decomposition, pattern recognition, abstraction, and algorithmic thinking, which are highly pertinent in assisting students in solving problems logically, systematically, and efficiently (Kaswar & Nurjannah, 2024).

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Despite the widespread recognition of the significance of computational thinking (CT), various studies indicate that students' CT abilities remain relatively low. Jamna et al. (2022) reported that 50% of ninth-grade students in Ternate City exhibited low CT abilities, while Sinaga (2022) identified students' competencies in decomposition, pattern recognition, abstraction, and algorithmic thinking as categorically low. In accordance with these findings, preliminary observations conducted by researchers at a junior high school in the Mataram area involving 24 seventh-grade students corroborated these observations. The test results revealed that none of the students were able to answer the test questions correctly. Notably, most students failed at the decomposition stage, which represents the initial step in problem-solving, hindering their ability to complete the questions accurately.

For illustrative purposes, consider the following test response from one student, as depicted in Figure 1.

A pyramid has a square base with a perimeter of 72 centimeters. If the slant height, TP , is 15 centimeters, determine the volume of the pyramid.

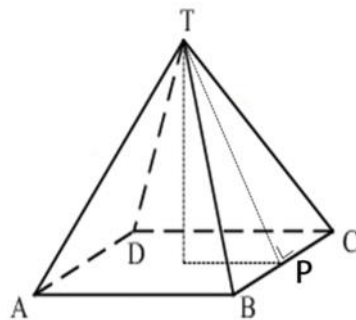


Figure 1. Example of a computational thinking test item for students

In the provided problem, students are tasked with systematically decomposing the problem. Specifically, they must first determine the height of the pyramid. To do this, they must comprehend the information given in the problem, including the length of the hypotenuse (TP) of the pyramid, which is 15 cm, and the circumference of the base, which is 72 cm. However, in the answer provided (Figure 2), students incorrectly write the length of TP as 15 cm and then proceed to calculate t as follows: $T = TP = \sqrt{TP^2 + P} = \sqrt{15^2 + 9}$. In the final equation, $\sqrt{15^2 + 9}$, it is evident that the value of “P” in the question is 9.

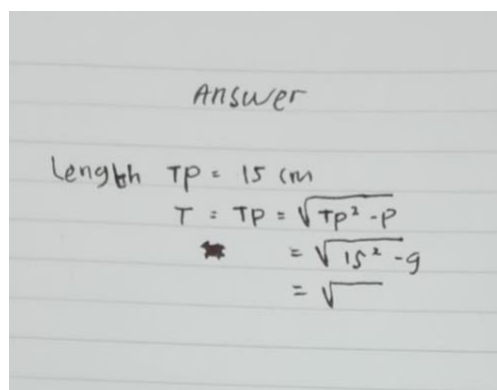


Figure 2. An example of a student's answer

It is important to note that the point “P” in the problem represents a point, not a line segment of the pyramid. Therefore, students mistakenly interpret “P” as a line segment, even though in the problem, “P” is only a point. This misinterpretation hinders students' ability to observe and understand the situation of the problem, demonstrating a lack of pattern recognition and abstraction skills.

Furthermore, students make an error by writing the equation $T = \sqrt{TP^2 + P}$ without systematically explaining how the value of P is obtained. To address this issue, students should follow these steps: (1) Determine the height of the pyramid first to calculate the volume of the pyramid. (2) Calculate the length of the base side from the known circumference of the base area. (3) Finally, determine the volume of the pyramid. This approach demonstrates that students' computational thinking abilities are relatively low. To mitigate this gap, selecting a suitable model and managing affective aspects is one potential solution that can be implemented.

Discovery Learning is a relevant learning model for developing computational thinking (CT) abilities. This model encourages students to actively engage in the process of concept discovery through exploration and hands-on experience, which has the potential to strengthen important aspects of CT (Sari, 2024). Empirical evidence from Nurhasanah et al. (2018) further demonstrates that the implementation of Discovery Learning significantly improves students' CT abilities. Through its emphasis on invention-oriented learning, this model provides opportunities for students to practice problem decomposition, identify patterns, develop abstractions, and construct algorithmic solutions independently. However, the effectiveness of Discovery Learning is greatly influenced by the ability of students to manage their learning process. This is where the role of self-regulated learning (SRL) becomes important. Zimmerman (2002) defines SRL as an active and systematic process that individuals engage in to direct their thoughts, motivations, and actions to achieve learning goals. Research by Rusdi et al. (2022) indicates that students with high SRL are more able to complete the CT stages completely than students with low SRL.

Although research on Discovery Learning (Sumarni, 2021) and self-regulated learning (SRL) (Andianti et al., 2021) has been conducted independently, studies that explicitly combine both approaches in the context of developing computational thinking (CT) are still limited and poorly documented in the literature. Schunk and Greene (2018) and Kramarski and Michalsky (2010) provide evidence that SRL abilities contribute to the improvement of higher-order thinking abilities, including the capacity to formulate algorithmic solutions and recognize patterns systematically. However, their studies did not directly address the integration of SRL with Discovery Learning to foster CT. Therefore, this research is crucial to address the identified literature gap and provide a novel perspective on the development of CT-based mathematics learning.

This study investigates the impact of the Discovery Learning model on students' computational thinking abilities in a specific grade level, considering the perspective of self-regulated learning. The findings indicate that the combination of Discovery Learning and high self-regulated learning resulted in enhanced computational thinking skills (Hariyani et al., 2024). This research aims to elucidate the interplay between learning strategies and student characteristics in fostering the development of computational thinking skills essential for the digital age.

METHOD

This study employed a quantitative approach with a quasi-experimental design. The method was selected because the assignment of students to experimental and control groups was not conducted randomly, yet still permitted a valid comparison of treatment effects. The study population consisted of 50 seventh-grade students. Samples were selected using a purposive sampling technique based on predetermined inclusion and exclusion criteria to ensure adequate representation. Class 7-A, comprising 26 students, was designated as the experimental class and received instruction utilizing the Discovery Learning model for 80 minutes per session across four meetings. This approach encompassed the stages of concept exploration, problem decomposition, pattern recognition, and algorithmic solution development. Class 7-B, consisting of 24 students, served as the control class and received conventional learning with the same duration and number of meetings, but adhering to standard instructional procedures. Following the completion of the solid geometry material, both groups were administered a test instrument designed to assess students' computational thinking (CT) abilities.

In this study, two research instruments were employed: a questionnaire and a test. The self-

regulated learning (SRL) questionnaire, adapted from Negara (2022), was developed in the form of a Likert scale to measure students' SRL levels during the learning process. It encompasses dimensions such as goal setting, self-monitoring, and self-evaluation.

The validity of the questionnaire was ensured through content and construct validity. Content validity was established by expert judgment of lecturers and mathematics teachers, while construct validity was confirmed by aligning it with established SRL frameworks and prior empirical evidence. The instrument had also undergone previous empirical testing for reliability, further assuring its suitability for this study.

To assess the extent to which students employ self-regulated learning (SRL) throughout the learning process, an SRL questionnaire is employed. This questionnaire is formulated based on indicators pertinent to the three primary phases within the SRL model, namely the planning, performance, and reflection phases (Pintrich & Zusho, 2007; Zimmerman, 2002). Each indicator is further elaborated into question items that elucidate aspects of students' self-directed learning strategies. The SRL questionnaire grid, which encompasses the indicators and the question items, is presented in Table 1.

Table 1. Self-regulated learning (SRL) questionnaire grid

Indikator	Statements
Forethought and Planning	Students precisely set the target score they aspire to attain in the subject. (+)
	Students fail to develop effective learning strategies when completing assigned tasks. (-)
	Students adhere to a consistent study schedule for each subject. (+)
	Students tend to prioritize studying when an examination is imminent. (-)
	Students are capable of independently completing the assignments assigned by their instructors. (+)
	Students hold the belief that academic success hinges on their unwavering responsibility in fulfilling the assignments prescribed by their instructors. (+)
	Upon completing the assignments assigned by the instructor, students are required to seek assistance from their peers. (-)
	Students perceive the assignments provided by the instructor solely as practice exercises, disregarding the importance of thorough execution. (-)
Performance Monitoring	Students strategically organize their learning environment to enhance their concentration. (+)
	Students have already acquired knowledge of the subject matter prior to the instructor's explanation. (-)
	Students often neglect or fail to prepare the necessary resources that can enhance their learning outcomes. (-)
	Students attend the lesson without having reviewed the material beforehand. (-)
	Students diligently study the learning material within the module until they attain a comprehensive understanding of its concepts. (+)
	Students have supplementary notes on the material covered in the module to facilitate comprehension and retention. (+)
	Students do not seek assistance from friends to comprehend material they have not yet grasped during lectures. (-)
Reflection on Performance	Students exhibit a lack of diligence in taking comprehensive notes on the pertinent material covered during the module. (-)
	Students persist in reading the subject matter within the module despite the unfavorable conditions. (+)
	Students persist in their studies of the subject, despite the perceived challenges it presents. (+)

The second instrument was a computational thinking (CT) test designed to assess students' problem-solving abilities in three-dimensional shapes (spatial geometry). The test was developed based on four computational thinking indicators: decomposition, pattern recognition, abstraction,

and algorithmic thinking. The instrument was constructed in the form of descriptive test items that necessitated students to articulate their reasoning processes during problem-solving. The CT test comprised several items aligned with each of the four indicators (Firza et al., 2025). For instance, an item for the decomposition indicator required students to subdivide a three-dimensional problem into smaller, more manageable components prior to proposing a solution. The blueprint or test grid for this instrument is presented in Table 2.

Table 2. Instrument grid of student computational thinking ability tests

KD	Indicator computational thinking	Question number	Question form
Solve problems related to the surface area and build volume of flat side spaces (cubes, beams), prisms and pyramids) as well as their combinations	Dekomposisi Pattern recognition Abstraksi Thinking algorithms	1,2	Description

In this study, descriptive statistics were employed to provide an overview of students' computational thinking (CT) abilities. Inferential statistics were utilized to address the research questions. Given the relatively small sample size and the non-normal data, nonparametric tests were employed. Specifically, the Mann-Whitney test was used for comparisons between two independent groups, while the Kruskal-Wallis test was applied for comparisons involving more than two groups. Prior to these analyses, assumption tests for normality and homogeneity of variance were conducted to ensure the appropriateness of the nonparametric approach.

RESULTS AND DISCUSSION

In accordance with the objectives of this study, several research questions were formulated as the primary focus of inquiry. The initial question pertains to the examination of disparities in students' computational thinking (CT) abilities between the group that received instruction utilizing the Discovery Learning model and the group that received instruction through conventional methodologies. The Mann-Whitney test was employed to compare the two independent groups, as the data did not adhere to a normal distribution.

To address the second and third research questions, the Kruskal-Wallis test was employed to compare more than two groups with non-normally distributed data. Specifically, this analysis examined the differences in students' CT abilities based on the level of self-regulated learning (SRL) and the interaction between the Discovery Learning model and SRL. The subsequent section provides a detailed description of the research findings.

Computational thinking ability based on the learning model

The implementation of the Discovery Learning model and conventional learning in distinct classes was conducted to assess the disparities in students' computational thinking abilities between the two learning groups. Figure 3 presents the distinctions in students' computational thinking abilities based on the chosen learning model.

As depicted in Figure 3, the descriptive analysis reveals that the computational thinking (CT) abilities of students in the experimental class, who underwent instruction through the Discovery Learning model, exhibited an average score of 67.60. Conversely, the control class, which received instruction employing the conventional model, demonstrated an average score of 62.82. This observation suggests that, overall, the students in the experimental class achieved approximately a 4.78-point higher level of proficiency compared to their counterparts in the control class.

The experimental class's score range spanned from 25.00 to 87.50, while the control class's ranged from 29.10 to 79.10. This disparity suggests that while the experimental class had students with low achievement, others achieved higher scores compared to the control class. This indicates

that Discovery Learning may encourage some students to attain optimal outcomes, albeit with an increased variation in achievement within the class.

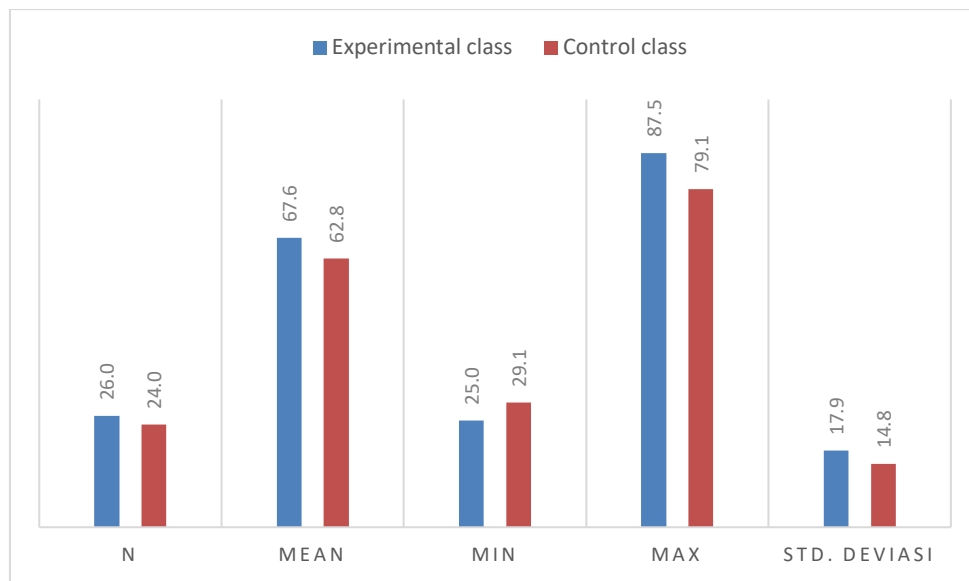


Figure 3. Descriptive statistics of computational thinking abilities based on discovery learning.

This is also reflected in the standard deviation values, where the experimental class exhibited a higher standard deviation of 17.92 compared to 14.85 in the control class. Consequently, the distribution of scores in the experimental class was more heterogeneous than in the control class. This suggests that the Discovery Learning model offers a broader opportunity for students to enhance their cognitive abilities; however, the success of students in utilizing this model is significantly influenced by their individual readiness and self-regulation skills.

To support the descriptive analysis, hypothesis testing was conducted subsequently employing statistical methods. The non-parametric statistical analysis utilized in this study was the Mann-Whitney test. The results of the analysis were obtained with the assistance of SPSS software, as presented in [Tables 3 and 4](#).

Table 3. Ranks of computational thinking ability based on learning model

	Learning model	N	Mean rank	Sum of ranks
Computational Thinking	Discovery learning	26	28,29	735,50
	Konvesional	24	22,48	539,50
	Total	50		

The Mann-Whitney test was conducted to assess the disparities in Computational Thinking abilities between students educated using the Discovery Learning model and those educated using the conventional model. The Ranks table indicates that the Discovery Learning group ($N = 26$) had a mean rank of 28.29, while the conventional group ($N = 24$) had a mean rank of 22.48 ([Table 3](#)). This suggests that, descriptively, students who received instruction through the Discovery Learning model exhibited higher Computational Thinking abilities compared to those who received instruction through the conventional model.

Furthermore, the statistical test results revealed that the Mann-Whitney U value was 239.500, with a Z-score of -1.437 and an Asymptotic significance (2-tailed) value of 0.151 ([Table 4](#)). Given that the significance value exceeded the significance level of 0.05 ($p > 0.05$), it can be concluded that there was no statistically significant difference between the Discovery Learning group and the conventional group in terms of Computational Thinking ability.

Although the analysis results indicated no statistically significant differences, the descriptive findings demonstrated that the Discovery Learning model produced higher average ranks compared to conventional learning. This aligns with constructivist theory, as noted by Lathifah et

al. (2024), who asserted that meaningful learning is more readily attained when students actively engage in concept discovery. This approach facilitates the practice of critical, logical, and systematic thinking, competencies closely associated with Computational Thinking.

Table 4. Statistical test of students' computational thinking ability based on learning model

	Computational thinking
Mann-whitney U	239,500
Wilcoxon W	539,500
Z	-1,437
Asymp. sig. (2-tailed)	0,151

Nevertheless, the non-significant results may have been influenced by several factors. Firstly, the sample size was relatively small (50 students), which may have limited the statistical power to discern meaningful differences. Secondly, variations in students' prior abilities and external factors (such as learning motivation or technological experience) could have impacted their Computational Thinking achievement. This aligns with previous studies (Rahmawati et al., 2023; Guggemos, 2021), which indicated that while innovative learning models possess the potential to enhance Computational Thinking, their results may not always be statistically significant when the sample size is restricted or when control variables are not adequately accounted for.

Consequently, the findings of this study suggest a promising correlation between the implementation of Discovery Learning and the development of Computational Thinking, albeit not yet statistically significant. These results can serve as a foundation for further research employing a larger sample size, more stringent variable control, and an extended instructional intervention period. This will enable a more comprehensive observation of the impact of the learning model on Computational Thinking.

Computational thinking ability based on self-regulated learning

This study examined the significance of self-regulated learning as a pivotal factor in determining learning success, particularly in the context of computational thinking abilities. Figure 4 presents a comparative analysis of students' computational thinking abilities across varying levels of self-regulated learning.

The descriptive analysis presented in Figure 4 elucidates a discernible disparity in students' Computational Thinking abilities, contingent upon their level of Self-Regulated Learning (SRL). Individuals exhibiting high SRL (N = 23) achieved an average score of 79.0, exhibiting a score range spanning from 75.0 to 87.5 and a standard deviation of 3.9. This observation suggests that a substantial majority of students within this category demonstrated exceptional Computational Thinking abilities, characterized by relatively narrow variations in their performance.

In the group of students with moderate SRL (N = 20), the average score obtained was 61.7, with a minimum score of 54.1 and a maximum of 66.6, and a standard deviation of 2.6. This average was lower than that of the high SRL group; however, the results were relatively consistent due to the relatively small variation.

Concurrently, students with low SRL (N = 7) exhibited the lowest average score, which was 30.9. Their score range spanned from 25.0 to 37.5, and their standard deviation was 4.1. This observation suggests that the low SRL group significantly trailed behind the other two groups in terms of Computational Thinking achievement.

Overall, there is a consistent pattern that the higher the level of students' self-regulated learning, the higher their computational thinking abilities. This finding reinforces the understanding that self-regulation in learning is a crucial factor influencing students' success in developing computational thinking skills.

Additionally, to bolster the aforementioned descriptive analysis outcomes, a non-parametric test, specifically the Kruskal-Wallis test, was employed in this study. This test was conducted to ascertain whether there were any disparities in students' Computational Thinking abilities

contingent upon the level of SRL. The analysis results were obtained utilizing SPSS software, as evidenced in Tables 5 and 6.

Table 5. Ranks computational thinking abilities based on self-regulated learning

Self regulated learning		N	Mean rank
Computational thinking	High	23	39,00
	Medium	20	17,50
	Low	7	4,00
	Total	50	

The Kruskal-Wallis test was employed to ascertain whether there were discernible disparities in Computational Thinking abilities among students based on their respective levels of Self-Regulated Learning (SRL), which were categorized into three distinct groups: high, medium, and low. As per the Ranks table, the high SRL group ($N = 23$) exhibited a mean rank of 39.00, the medium SRL group ($N = 20$) had a mean rank of 17.50, and the low SRL group ($N = 7$) had a mean rank of 4.00. These descriptive statistics suggest that, on a general level, there is a positive correlation between students' levels of self-regulated learning and their Computational Thinking abilities.

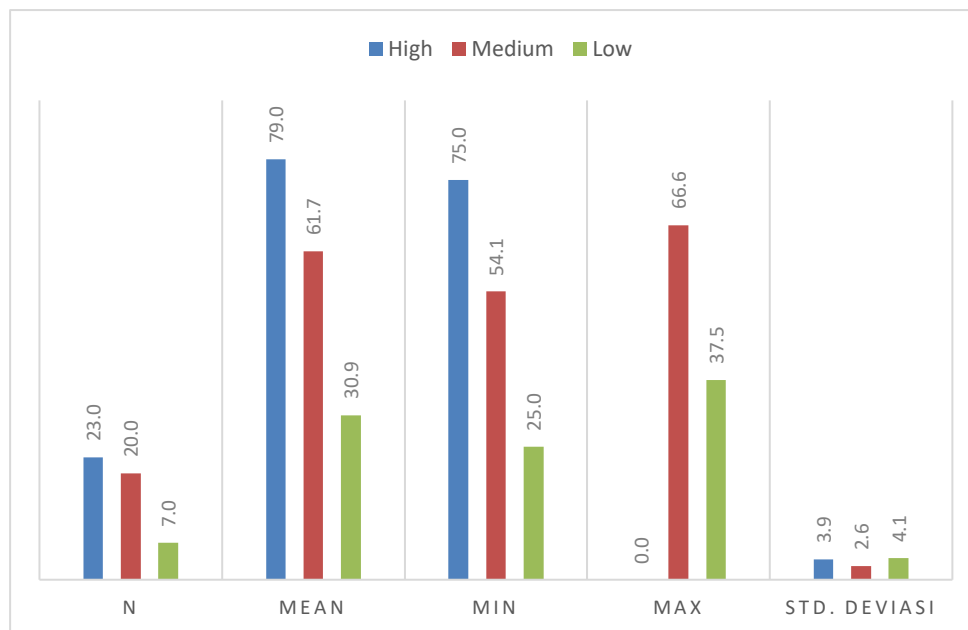


Figure 4. Descriptive statistics of computational thinking abilities based on self-regulated learning

The statistical test results indicated that the Kruskal-Wallis value was $H = 42.662$, with degrees of freedom (df) equal to 2 and an asymptotic significance level (Asymp. Sig.) of 0.000. Given that the significance value ($p < 0.05$) was less than the predefined significance level, it is statistically significant to conclude that there exists a substantial difference in Computational Thinking abilities based on the level of self-regulated learning. Consequently, students' levels of self-regulation in the learning process exert a significant impact on their computational thinking outcomes.

Table 6. Statistical test of computational thinking ability based on self-regulated learning

Computational thinking	
Kruskal-wallis H	42,662
df	2
Asymp. sig	0,000

The findings of this study suggest that students with high levels of self-regulated learning (SRL) exhibit significantly enhanced computational thinking (CT) abilities compared to those with moderate or low SRL. This observation aligns with Zimmerman's (2002) self-regulated learning theory, which posits that students with robust self-regulation skills possess the capacity to establish objectives, select appropriate strategies, monitor, and assess their own learning processes. Consequently, they can cultivate systematic, logical, and reflective thinking—essential components of computational thinking. Furthermore, this result corroborates recent findings by Yu (2023), who underscores the pivotal role of self-regulation in augmenting learning effectiveness, particularly in independent and technology-driven learning environments. Students with high SRL demonstrate heightened adaptability and the ability to optimize their learning outcomes. Collectively, both Zimmerman's seminal theory and Yu's contemporary evidence emphasize the significance of SRL in the development of higher-order thinking skills, including computational thinking.

A notable distinction also underscores the pivotal role of self-regulated learning in the success of problem-based learning, algorithmic reasoning, and the exploration of solution strategies. Individuals with low self-regulated learning tend to exhibit passive behavior, lack intrinsic motivation, and encounter difficulties in managing learning strategies, consequently resulting in diminished computational thinking performance. Conversely, students with high self-regulated learning demonstrate enhanced ability to identify problems, formulate solutions, and reflect on the executed steps—all of which are fundamental components of computational thinking.

These findings align with numerous previous studies demonstrating a positive correlation between self-regulation and enhanced higher-order thinking abilities. Self-regulation facilitates students' proactive planning, monitoring, and reflection on their learning processes (Schunk & Greene, 2018; Kramarski & Michalsky, 2010). Within the context of mathematics and technology education, self-regulated learning supports students in consistently practicing diverse strategies, rectifying errors, and formulating innovative solutions—activities that are highly pertinent to the practice of Computational Thinking.

Consequently, these findings suggest that strengthening self-regulated learning should be a primary consideration in the design of learning activities intended to foster Computational Thinking. Educators can facilitate this process through the practice of reflection, the provision of constructive feedback, and the development of students' independent learning strategies.

Interaction between learning model and self-regulated learning on computational thinking ability

Simultaneous observation, or observation to examine the interaction, was conducted to identify the combination of the learning model and self-regulated learning in this study. This observation provides valuable information for developing effective strategies to adapt to students' levels of self-regulated learning. Table 7 presents computational thinking ability based on the learning model and self-regulated learning.

The findings presented in Table 7 demonstrate distinct variations in Computational Thinking achievement, contingent upon the interplay between the employed learning models (Discovery Learning and Conventional) and the level of Self-Regulated Learning (SRL).

Table 7. Computational thinking ability based on learning model and self-regulated learning

Model pembelajaran	Self regulated learning	Mean	Std. deviation	N
Discovery learning	High	79,4000	4,42312	16
	Medium	59,7000	3,42929	6
	Low	32,2750	5,23856	4
	Total	67,6038	17,92017	26
Konvensional	High	77,9286	2,00060	7
	Medium	62,4929	1,62787	14
	Low	29,1000	,00000	3
	Total	62,8208	14,84552	24

Within the high SRL group, students who utilized the Discovery Learning model achieved an average score of 79.40, with a standard deviation of 4.42. Conversely, students who employed the conventional model attained an average score of 77.93, accompanied by a standard deviation of 2.00. This empirical evidence suggests that the Discovery Learning approach yielded marginally higher achievement compared to the conventional model. However, it is noteworthy that the variability within the Discovery Learning group was more pronounced than in the conventional group, implying that not all students within this group experienced uniform improvement.

In contrast to the high SRL group, the moderate SRL group demonstrated higher achievement with the conventional model compared to Discovery Learning. The average Computational Thinking score for the conventional model was 62.49 (SD = 1.63), while for Discovery Learning, it was 59.70 (SD = 3.43). Although this difference is not substantial, the conventional model exhibited more consistent performance, as evidenced by its smaller standard deviation. This suggests that students with moderate SRL tend to have more stable computational thinking performance when adhering to a conventional learning approach.

In the low SRL group, Discovery Learning demonstrated superior outcomes compared to the conventional model. The average Computational Thinking score of students enrolled in Discovery Learning was 32.28 (SD = 5.24), while in the conventional model, it was only 29.10 (SD = 0.00). Although both scores remain relatively low in absolute terms, Discovery Learning provided a modest improvement in achievement, albeit accompanied by greater variability. Conversely, students' performance in the conventional model exhibited consistency, albeit at a low achievement level.

In general, the average Computational Thinking achievement of students in the Discovery Learning model was 67.60, while in the conventional model it was 62.82. These findings suggest that Discovery Learning is more effective in enhancing computational thinking abilities compared to conventional learning. Specifically, Discovery Learning is more beneficial for students with high and low self-regulated learning (SRL), while for students with moderate SRL, conventional learning appears to yield better results.

To corroborate the aforementioned descriptive analysis, the Kruskal-Wallis test was conducted once more. The outcomes of the Kruskal-Wallis test, which were obtained using SPSS software, are presented in [Tables 8](#) and [9](#).

Table 8. Ranks students' computational thinking abilities based on learning model and self-regulated learning

	Interaction ranks	N	Mean rank
Computational thinking	High discovery learning	16	39,47
	Medium discovery learning	6	14,17
	Low discovery learning	4	4,75
	High conventional	7	37,93
	Medium conventional	14	18,93
	Low conventional	3	3,00
	Total	50	

The results presented in the table above, derived from the Kruskal-Wallis test, demonstrate a substantial disparity in Computational Thinking achievement when considering the interplay between the learning model and the level of Self-Regulated Learning ($p < 0.05$). This indicates that variations in students' Computational Thinking attainment are not solely attributable to the learning model itself but are also influenced by the students' Self-Regulated Learning level and the concomitant interaction between these factors.

From a mean rank perspective, the highest achievement is attained in the Discovery Learning category, characterized by high SRL, with a mean rank of 39.47. This is followed by the Conventional category, also exhibiting high SRL, with a mean rank of 37.93. Conversely, the lowest achievement is observed in the Conventional category, characterized by low SRL, with a mean

rank of 3.00. Discovery Learning, on the other hand, also exhibits low SRL, resulting in a mean rank of 4.75.

Notably, within the medium SRL group, students employing conventional learning strategies exhibit a higher mean rank (18.93) in comparison to Discovery Learning, which registers a lower mean rank of 14.17. This observation suggests that the efficacy of the learning model is significantly influenced by the students' level of self-directed learning.

Table 9. A statistical test of students' computational thinking ability based on learning model and self-regulated learning.

	Computational thinking
Kruskal-wallis H	43,211
df	5
Asymp. sig.	0,000

The results presented in the table above, derived from the Kruskal-Wallis test, demonstrate a substantial disparity in Computational Thinking achievement when considering the interplay between the learning model and the level of Self-Regulated Learning ($p < 0.05$). This indicates that variations in students' Computational Thinking attainment are not solely attributable to the learning model itself but are also influenced by the students' Self-Regulated Learning level and the concomitant interaction between these factors.

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The findings of this study align with previous research indicating that students' computational thinking (CT) abilities remain at a subpar level. Jamna et al. (2022) reported that 50% of ninth-grade students in Ternate City exhibited low CT abilities. Similarly, Sinaga (2022) identified students' competencies in decomposition, pattern recognition, abstraction, and algorithmic thinking as categorically low. These findings were corroborated by preliminary observations conducted by the researchers at a junior high school in the Mataram area, involving 24 seventh-grade students. Notably, none of the students were able to answer the test questions correctly. The majority of students encountered difficulties at the decomposition stage, which represents the initial step in problem-solving. This impediment hindered their ability to complete the questions accurately.

These studies essentially corroborate a fundamental issue pertaining to the limited proficiency of students in cognitive technology (CT) abilities. However, previous research primarily concentrated on descriptive aspects, specifically detailing the condition of CT skills without delving into the factors that could potentially enhance their improvement. In contrast, the findings of this study substantiate that Discovery Learning is more effective when applied to students with both high and low self-regulated learning (SRL) abilities. Within the high SRL group, students who utilized Discovery Learning attained the highest CT scores compared to all other categories. This aligns with the inherent characteristics of Discovery Learning, which necessitates self-regulation, initiative, and activeness in exploring concepts, thereby enabling students with high SRL to fully capitalize on the benefits of this model.

In contrast, within the low SRL group, while the CT achievement remains relatively low, Discovery Learning (DL-R) yields a higher score compared to Conventional (Konv-R). This

suggests that the characteristics of Discovery Learning, which provide exploration opportunities despite their challenging nature, can still motivate students with low SRL to exhibit greater active engagement compared to conventional learning, which generally tends to be passive.

In contrast, within the medium SRL group, conventional learning actually yields superior outcomes compared to Discovery Learning. This disparity can be attributed to the fact that students with medium SRL may still require more structured guidance. The conventional model, which emphasizes direct instruction and teacher supervision, instills a sense of security and clarity in the learning process, resulting in more consistent CT achievement when compared to the challenges of independence encountered in Discovery Learning.

Consequently, it can be inferred that the interplay between the learning model and SRL significantly influences the attainment of Computational Thinking abilities. Discovery Learning is more appropriate for students with high and low SRL, while the conventional model is more suitable for students with medium SRL. The disparity in CT achievement underscores the necessity of adaptive learning strategies, wherein educators consider not only the learning model but also the students' level of self-regulation.

CONCLUSION

The findings of this study indicate that students' Computational Thinking (CT) abilities are influenced by the learning model employed, the level of Self-Regulated Learning (SRL), and the interplay between these factors. From a learning model perspective, the implementation of Discovery Learning is demonstrated to be more effective in enhancing CT achievement compared to the conventional model. This observation is particularly pronounced in groups of students with varying levels of SRL, as Discovery Learning facilitates the development of independent thinking skills, problem exploration, and solution generation in a more structured manner.

When analyzed through the lens of self-regulated learning (SRL), students with a high level of SRL demonstrated the highest cognitive test (CT) scores compared to students with medium or low SRL. Conversely, students with low SRL exhibited the lowest CT achievement. However, within this low SRL group, Discovery Learning still yielded a more significant impact compared to the conventional model. This observation suggests that the level of self-regulated learning significantly influences the development of CT abilities, irrespective of the learning model employed.

Additionally, the interaction analysis demonstrated that the learning model and SRL mutually influence students' cognitive test achievement. Discovery Learning was found to be more effective for students with high or low SRL, while for students with moderate SRL, the conventional model tended to yield relatively better results. This suggests that the effectiveness of learning is not solely determined by the model employed but also by the students' self-regulation characteristics during the learning process.

These findings have both theoretical and practical implications. Theoretically, they reinforce the significance of integrating active learning models with self-regulation strategies to foster higher-order thinking abilities. Practically, educators can employ Discovery Learning while considering students' self-regulation levels to optimize learning outcomes, accordingly tailoring guidance and support.

Despite these contributions, the study presents certain limitations. The sample size was restricted, which may have compromised the generalizability of the findings. Additionally, the instruments employed were confined to essay tests and questionnaires, potentially overlooking the full spectrum of computational thinking skills in real-world or technologically enhanced settings. Future research is advisable to include larger and more representative samples, incorporate more comprehensive assessment tools such as project-based or digital tests, and investigate additional factors that influence computational thinking, including learning motivation and individual learning preferences.

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