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SELF-REGULATED LEARNING AND COMPUTATIONAL THINKING: ANALYZING THE PERFORMANCE OF JUNIOR HIGH SCHOOL STUDENTS ON PISA-LIKE PROBLEMS

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Abstrak
Penelitian ini menganalisis hubungan antara self-regulated learning (SRL) dan *computational thinking* (CT) dalam memecahkan masalah matematika seperti soal PISA di antara siswa sekolah menengah pertama. Penelitian ini merupakan penelitian kualitatif, data dikumpulkan dari 33 siswa kelas sembilan melalui kuesioner SRL, soal PISA-Like, think aloud, dan wawancara semi-terstruktur. Siswa dikategorikan ke dalam tiga tingkat SRL: tinggi (12,12%), sedang (72,73%), dan rendah (15,15%). Dua siswa dari setiap kategori dipilih untuk analisis mendalam guna memastikan representasi yang seimbang di seluruh kelompok dan untuk menangkap beragam pola kinerja pemikiran komputasional. Analisis difokuskan pada empat indikator CT: dekomposisi, pengenalan pola, abstraksi, dan pemikiran algoritmik. Hasil penelitian menunjukkan bahwa siswa dengan SRL tinggi mampu menetapkan tujuan yang jelas, efektif, dan menyempurnakan strategi yang memungkinkan untuk menggeneralisasi pola dan membuat algoritma yang efisien. Siswa SRL sedang menunjukkan kemampuan CT sedang, meskipun secara tidak konsisten dalam strategi dan penalaran. Siswa dengan SRL rendah menunjukkan keterampilan CT yang lemah dan tidak memiliki pendekatan pemecahan masalah yang sistematis. Temuan ini menyoroti peran penting SRL dalam mendukung kemampuan siswa menerapkan CT dalam konteks matematika yang kompleks. Penelitian selanjutnya dapat mengeksplorasi kemampuan SRL untuk meningkatkan perkembangan CT di berbagai domain matematika.
Kata kunci: *Computational Thinking*; *Self-regulated learning*; Soal PISA-Like.

Abstract
This study examines how self-regulated learning (SLR) relates to computational thinking (CT) in solving PISA-like problems. Using a qualitative descriptive design, data were collected from 33 ninth-grade students through SRL questionnaires, PISA-like problem-solving tasks, think-aloud protocols, and semi-structured interviews. Students were categorized into three SRL levels: high (12.12%), medium (72.73%), and low (15.15%). Two students from each level were selected for in-depth analysis to ensure a balanced representation across groups and to capture diverse patterns of

computational thinking performance. The analysis focused on four CT indicators: decomposition, pattern recognition, abstraction, and algorithmic thinking. Results showed that high-SRL students set clear goals, effectively monitored their work, and refined their strategies, enabling them to generalize patterns and construct efficient algorithms. Medium-SRL students displayed moderate CT ability, often identifying relevant patterns but struggling to consistently plan or evaluate their solutions. Students with low SRL exhibited weak CT skills and lacked systematic problem-solving approaches. These findings highlight the significant role of SRL in supporting students' ability to apply CT in complex mathematical contexts. Future studies may explore digital SRL scaffolding tools to enhance CT development across diverse mathematical domains.
Keywords: Computational Thinking; Self-Regulated Learning; PISA-Like Problems.

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INTRODUCTION

In recent decades, advances in information and communication technology (ICT) have significantly reshaped global education systems. In Indonesia, the integration of ICT into classrooms has not only expanded access to digital learning resources but also reshaped teaching and learning practices toward more student-centered approaches. For example, the use of digital platforms, interactive e-modules, and online collaborative tools has provided opportunities for students to engage in inquiry-based tasks, practice higher-order thinking, and solve real-world problems in mathematics and science classes. These changes reflect the demands of 21st century education, which emphasizes not only the mastery of knowledge, but also skills to face increasingly complex challenges in a knowledge- and technology-based world (Kurniati et al., 2024; My Nguyen et al., 2024; Posicelskaya, 2023; Santika Lya Diah Pramesti, 2024). One of the major challenges lies in cultivating higher order thinking skills that not only enhance students' cognitive development but also equip them to addres authentic, real life challenges. Among the various skills that are increasingly being prioritized, Self-Regulated Learning (SRL) and Computational Thinking (CT) have become two key skills that have gained major attention in educational research.

Self-regulated learning (SRL) refers to the process in which individuals actively control and monitor their learning activities to achieve academic goals (Schunk & Zimmerman, 1998). SRL focuses on students' ability to organize themselves in the learning process, from planning, timing, recording, and evaluating their own understanding. Students who master SRL are more likely to be able to learn independently, set their own learning goals, and reflect to improve their understanding of the material being studied (Cassidy, 2011). In technology-enhanced learning environments, these skills are essential, as students must not only comprehend information but also leverage digital tools to access resources, manage their time, and evaluate their learning processes and outcomes.

On the other hand, Computational Thinking (CT) is a thinking skill that involves the ability to solve problems through computer-based approaches, such as using algorithms, programming and data structures to solve complex problems (Mukasheva & Omirzakova, 2021). *Computational Thinking* is often associated with the field of computer science, but in reality, CT also plays an important role in learning mathematics (Denning & Tedre, 2021; Looi et al., 2024). Processes such as breaking down complex problems into simpler parts (decomposition), recognizing patterns, generalizing (abstraction), and designing systematic steps to solve problems (algorithms) are CT practices that are in line with the problem solving approach in mathematics (Rich et al., 2020; Sneider et al., 2014). Therefore, the integration of CT in mathematics learning can strengthen students critical and analytical thinking skills in understanding concepts and solving contextual problems (Santika Lya Diah Pramesti, 2024; Susanti et al., 2025), including those equivalent to the PISA assessment.

The rapid development of information technology has required students to not only passively master knowledge, but also to develop higher order thinking skills, including CT. One of the international instruments used to measure students' ability to face real-world challenges is the Program for International Student Assessment (PISA) (Putri et al., 2024; Salwadila & Hapizah, 2024; Whitney-Smith, 2023). One of the aspects measured in PISA is students' ability to solve complex and applied problems, which reflects critical thinking skills and the ability to use knowledge in real-world contexts (OECD, 2023) .

However, although PISA provides a broad picture of students' abilities in different countries, there are major challenges in understanding how skills such as SRL and CT affect students' performance on the exam (ÖZDEMİR & ÖNAL, 2022). For example, although SRL can help students to become more independent and responsible in learning, not many studies have examined how SRL and CT interact to improve students' performance on complex questions(Pasterk & Benke, 2024). SRL refers to students' ability to independently set learning goals, monitor progress, and evaluate and reflect on their learning outcomes (Araka et al., 2020). Meanwhile, CT involves a logical and systematic approach to problem solving, including decomposition, pattern recognition, abstraction, and algorithm formulation (Goos et al., 2023; Na et al., 2024; Seckel et al., 2022).

Many studies highlight the importance of SRL in improving academic performance, but few discuss how SRL can be applied in the context of computational thinking or technology-based problem solving. This is a gap that needs to be filled in current educational research. Research examining the relationship between SRL and CT is particularly important in the context of junior secondary education, where students begin to learn to develop higher critical thinking skills. At the junior high level, students have not yet fully mastered the more complex concepts of mathematics or science, yet they are faced with the challenge of solving problems involving these basic concepts, often in the form of more applied problems (Looi et al., 2024; Richardo et al., 2025; Salwadila & Hapizah, 2024). In other words, at this level, students should be able to connect theoretical knowledge with practical application in the real world. Therefore, it is important to understand how the ability to organize and monitor their learning process (SRL) can support the application of CT in more complex problem solving (Kong & Wang, 2024; M. Gunawan Supiarmo et al., 2021).

One way to evaluate students' ability to solve more applicable problems is to use PISA-like questions, which are designed to test critical thinking skills and the ability to solve problems relevant to the real world. PISA questions measure not only students' factual knowledge, but also their ability to apply that knowledge in more contextualized and complex situations (Nusantara & Putri, 2021; Ozkale & Ozdemir Erdogan, 2022). Therefore, students' performance in PISA-Like questions can be a good indicator to assess the extent to which SRL and CT can help students in solving more abstract and technology-based problems in the 21st century learning challenges.

Although previous studies have examined SRL in general learning contexts and explored CT in relation to digital literacy and programming, very few investigations have analyzed how these two constructs interact in shaping students' problem-solving performance, particularly when dealing with PISA-like tasks. Existing studies tend to treat SRL and CT as separate skills, leaving a gap in understanding how students self-regulation processes support or hinder the cognitive steps involved in computational thinking when solving complex, real-world mathematical problems. Moreover, research focusing on junior high school learners remains limited, even though this developmental stage is critical for the formation of both SRL and CT skills. This gap highlights the need for empirical evidence that explains the interplay between SRL and CT in the context of PISA-like mathematics tasks, which is precisely the focus of the present study.

Self-Regulated Learning (SRL) is an active process carried out by individuals in organizing thoughts, feelings, and actions in a planned manner to achieve learning goals independently (Santrock, 2007; Schunk & Zimmerman, 1998). SRL involves metacognitive, motivational, and behavioral components, which enable students to design learning goals, monitor, and evaluate their learning processes and results (Panadero, 2017). According to Pintrich & De Groot (1990), SRL consists of four phases: planning, monitoring, control, and evaluation, which include cognitive strategies, emotion regulation, and management of the learning environment. Individuals with high SRL tend to have intrinsic motivation, manage time effectively, use appropriate learning strategies, and are able to solve problems reflectively (Karlen & Hertel, 2024; Montalvo, F. T. & Torres, 2004). In the context of mathematics learning, SRL is very important to increase the effectiveness and independence of student learning in the digital era. Indicators of SRL according to Parantika And Sariyasa (2022) include initiative and motivation to learn, target setting, monitoring, learning strategies, evaluation, and the ability to adjust the learning environment independently.

Wing (2006) suggests that Computational Thinking is the ability to think in a structured and systematic way to solve problems that can be applied to various disciplines, not just in the computer field. CT involves the ability to understand problems thoroughly, break down problems into smaller parts, and develop structured and efficient solutions (Kjällander et al., 2021; Mannila et al., 2014; Ye et al., 2023). As a skill based on logic and algorithms, CT provides a foundation for students to develop in various fields, such as computer programming, data processing, and technology development (Moon et al., 2023). Indicators of computational thinking according to Ng et al. (2023), van Borkulo et al. (2019), and Wing (2006) include:

a. Problem decomposition is one of the skills in decomposing complex information or data into smaller parts, making it easier to understand, evaluate, solve, and develop separately so that it will be easier to understand a problem.
b. Algorithmic thinking is the skill to analyze problems and prepare the steps to be taken so that the right solution can be obtained.
c. Pattern recognition is one of the abilities to identify, recognize, and develop patterns, relationships or similarities to understand data and strategies used to understand large data and can strengthen abstraction ideas.
d. Abstraction and Generalization, Abstraction is related to making meaning from the data found and its implications. While Generalization is the ability to

conclude patterns that have been found and formulate a pattern in general in order to solve new problems.

This research has the potential to provide deeper insights into how SRL and CT development can be integrated in the junior secondary education curriculum, especially to prepare students for the increasingly complex challenges ahead. By examining how these two skills interact and support each other in the problem-solving process, this research will not only enrich the academic literature on technology-based learning, but also provide practical insights for educators and policy makers to design more effective learning interventions.

METHOD

This research employed a qualitative descriptive method to deeply explore the computational thinking (CT) abilities of junior high school students based on their levels of self-regulated learning (SRL), as this approach allows for a detailed examination of students' reasoning processes and problem-solving strategies elements that cannot be fully captured through quantitative measures. The use of a qualitative approach was justified academically by the need to uncover in-depth and contextualized insights into students thought processes something that quantitative methods may not fully capture. Furthermore, the grouping of students into SRL categories (high, medium, low) allowed for meaningful comparisons of CT indicators across varied levels of learning autonomy, in line with the theoretical model of SRL by Zimmerman and the framework of computational thinking by Grover & Pea (2013) (Grover & Pea, 2013).

The research subjects were 33 ninth-grade students from SMP Negeri 6 Pekalongan, selected using purposive sampling, because the school has a heterogeneous student population in terms of academic ability and has implemented technology enhanced mathematics learning, making it suitable for examining variations in SRL and computational thinking. This sampling technique was chosen to ensure that participants met specific criteria relevant to the study's objectives, namely students who had already mastered prerequisite mathematics content such as numbers and social arithmetic, and who were able to articulate their reasoning both verbally and in written form. These criteria were important because the study focused on analyzing students self-regulated learning and computational thinking (CT) through PISA-like problem-solving tasks, which required not only sufficient prior mathematical knowledge but also the ability to explain strategies and reflect on problem-solving processes. By applying purposive sampling, the research was able to include students most likely to provide rich and reliable data for in-depth qualitative analysis. From these, six students (two from each SRL category) were chosen for in-depth analysis, following SRL-level classification through a validated questionnaire. The decision to categorize subjects was grounded in the need to identify distinct SRL profiles and how these profiles influence the application of CT indicators during problem solving.

Data were collected through several instruments. First, an SRL questionnaire adapted from I.W.A Parantika, Sariyasa (2022), consisting of 25 items measuring cognitive, motivational, and behavioral aspects of self-regulated learning. This questionnaire demonstrated strong content validity based on expert judgment and acceptable internal consistency as indicated by Cronbach's alpha. Second, a PISA-like mathematics test comprising two open-ended problems in the number content domain was administered to elicit students' computational thinking (CT) processes. The questions were intentionally designed to represent the four CT components—decomposition, abstraction, pattern recognition, and algorithmic thinking—so that each item required students to break down information, identify essential elements, recognize numerical or structural patterns, and construct logical solution steps. This design ensured that the tasks not only assessed mathematical skills but also explicitly activated CT components relevant to the study. The test showed high content validity (V-Aiken > 0.8), indicating strong expert agreement on item relevance, and moderate reliability (Cronbach's alpha = 0.614). Third, think-aloud protocols were used during problem solving to capture students' immediate cognitive processes and reveal how CT elements were applied in real time. Finally, semi-structured interviews were conducted to triangulate the findings and clarify students' reasoning strategies, thereby strengthening the overall credibility of the data.

To guide the analysis, four computational thinking indicators were used, as shown in the following table. These indicators were selected because they represent the core components of CT (Wing, 2006): decomposition, pattern recognition, abstraction, and algorithmic thinking, which are widely recognized in the literature as essential cognitive processes for solving complex mathematical problems.

Table 1. Indicators of Students' Computational Thinking Processes in solving PISA-LIKE Numbers Content

No.	Computational Thinking Indicator	Sub Indicators
1	Decomposition	Students are able to identify and simplify the given PISA-Like Numbers Content problem by dividing it into several parts, namely what is known and questioned from the given problem
2	Pattern Recognition	Students are able to find similarities or differences in patterns, which they then use to develop solutions to problems.
3	Abstract	Students can find the conclusion by eliminating elements that are not needed When implementing the problem-solving plan
4	Algorithmic Thinking	Students can explain the logical and structured steps they followed to solve the given problem.

Data were analyzed using the Miles and Huberman (2014) model, which involves three iterative stages: (1) data reduction, where raw data from questionnaires, tests, think-aloud protocols, and interviews were coded and categorized; (2) data display, in which organized matrices and excerpts were used to compare CT performance across SRL levels; and (3) conclusion drawing, where emerging patterns were interpreted to develop coherent findings about the SRL–CT relationship. To enhance the credibility and depth of interpretation, triangulation was applied across instruments (questionnaires, tests, interviews) and data sources (written work, verbal explanations, observational notes). Limitations of this study include the small sample size (six focal participants) and the single school setting, which may affect the generalizability of findings. Additionally, the study relied heavily on students' ability to verbalize their thoughts, which might disadvantage students with communication difficulties despite having cognitive strength.

Implications suggest that math educators should explicitly integrate SRL development into instruction, using CT-based problem solving as a context to foster metacognitive awareness, motivation, and strategic behavior. The research also recommends the use of think-aloud and reflection techniques to enhance students' awareness of their own learning processes.

Future research should consider expanding the participant pool, incorporating longitudinal designs, and applying mixed methods to further validate the interrelationship between SRL and CT across various mathematical topics.

RESULT AND DISCUSSION

Data on students' computational thinking skills obtained from each research subject included the results of written test answers, and interview recordings. The interview recordings were converted into interview transcripts. The transcripts were labeled to facilitate the data analysis process. The labeling of interview transcripts is as follows.

$$\underbrace{\text{ST/SS/SR}}_{\text{I}} \quad \underbrace{1/2}_{\text{II}} \quad \underbrace{\text{D/B/P/A}}_{\text{III}}$$

Description:

ST/SS/SR : *Stating the level of self-regulated learning of research subjects, namely research subjects with high self-regulated learning (ST), research subjects with moderate self-regulated learning (SS), research subjects with low self-regulated learning* (SR).

1/2 : *States the order of research subjects*

D/B/P/A : *States the subject's computational thinking steps of decomposition (D), algorithmic thinking (B), pattern recognition (P), and abstraction (A).*

After administering the self-regulated learning scale, researchers grouped students who had high, medium, and low levels of self-regulated learning ability. The grouping of students' SLR ability categories can be seen in Table 2.

Table 2. Grouping of Students' *Self-regulated Learning*

Self-regulated learning category	Interval (n)
High	$n \geq 121{,}66$
Medium	$108{,}45 < n < 121{,}66$
Low	$n \leq 108{,}45$

Based on the data collected, of the 33 ninth-grade students at SMP Negeri 6 Pekalongan, 5 students (15.15%) demonstrated low self-regulated learning, 24 students (72.73%) showed moderate levels, and 4 students (12.12%) exhibited high self-regulated learning. After giving the computational thinking test using PISA-Like questions, researchers grouped students who had high, medium, and low levels of computational thinking ability. The grouping of student computational ability categories can be seen in Table 3.

Table 3. Grouping of students Computational thinking ability

CT Ability Category	Interval (n)
High	$n \geq 86{,}529$
Medium	$38{,}527 < n < 86{,}529$
Low	$n \leq 38{,}527$

Based on the research data, among the 33 students of class IX D at SMP Negeri 6 Pekalongan, 6 students (18.18%) demonstrated low computational thinking ability, 22 students (66.67%) showed moderate ability, and 5 students (15.15%) exhibited high computational thinking ability. This shows that students in class IX D of SMP Negeri 6 Pekalongan predominantly achieved moderate computational thinking ability.

The overall results indicate that students generally performed well on decomposition, pattern recognition, and algorithmic thinking, but showed weaker performance in abstraction and generalization. This pattern provides the basis for the subsequent in-depth analysis of students at different SRL levels. At the interview stage, only two subjects from each level of students' *self-regulated learning* were taken, with details in Table 4 as follows:

Table 4. Research Subject Data

Subject Code	Score	CT capability	Subject Characteristics
ST1	85,71	Medium	Olympic bound student who refuse to give up
ST2	78,57	Medium	Not giving up easily
SS1	71,43	Medium	Take the test in a relaxed manner
SS2	92,86	High	Olympic student, taking the test in a relaxed manner
SR1	57,14	Medium	Easy to give up
SR2	50	Low	Restlessness and giving up easily

ST, SS, and SR demonstrated the ability to meet the indicators of decomposition and algorithmic thinking in computational thinking, although SR still showed some shortcomings and errors. ST and SS also met the pattern recognition indicators, despite SS making some mistakes. Additionally, ST was able to meet the indicators of abstraction and pattern recognition, though not without errors. These findings align with studies by M. Gunawan Supiarmo et al., (2021); Mubarokah et al., (2023); Rijal Kamil et al., (2021), which states that students in the high category tend to meet the indicators for *Decomposition* and *pattern recognition*, but perform less accurately in *Algorithmic* and *Debugging*.

High SRL Student (ST)

ST1 and ST2 is a student who has high self-regulated learning ability. The achievement of ST1 and ST2 in solving PISA-Like questions on number content is described as follows:

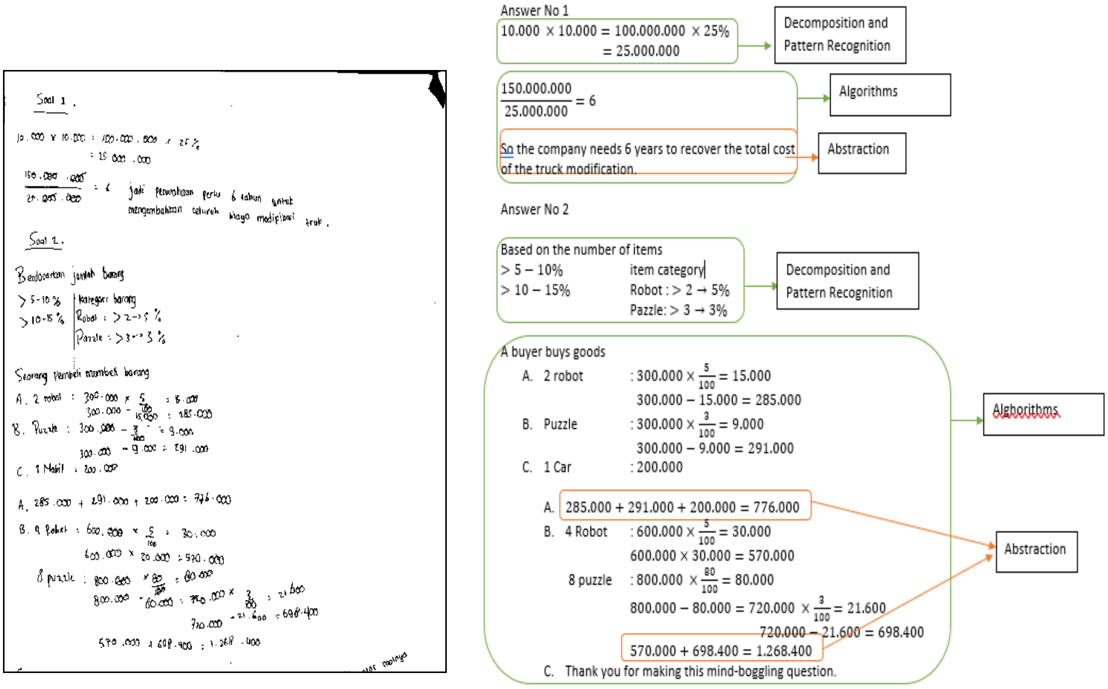

Figure 1. ST1 answers

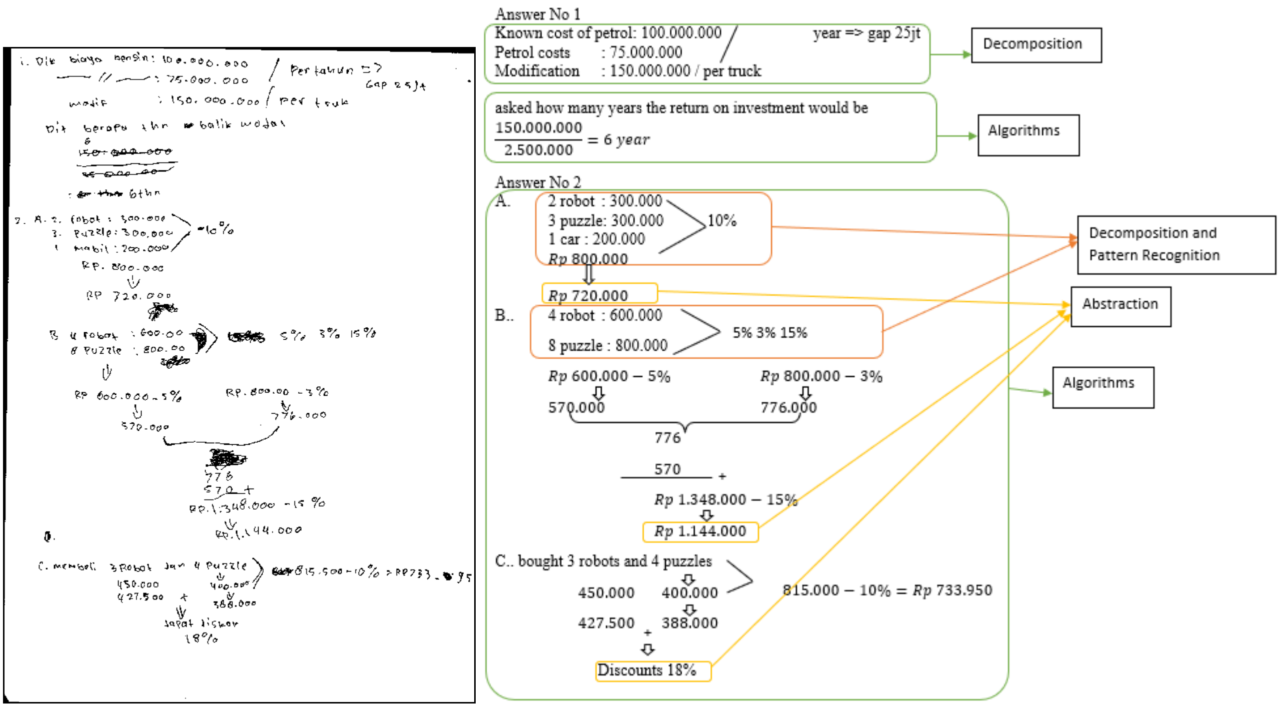

Figure 2. ST2 answers

Based on figure 1 and figure 2, students ST1 and ST2 showed high mastery of *Computational Thinking* skills in almost all indicators. In the process of solving the PISA-Like question on number content, ST1 showed good decomposition ability, able to identify known and asked information and simplify the question into small logical parts. However, despite trying to recognize the calculation pattern, ST1 has not been able to state it explicitly in the form of a general strategy or formula. In the abstraction aspect, ST1 has been able to filter out important information, but has not transformed it into a more efficient form such as a general mathematical representation. ST1 also showed a logical sequence of solution steps, although not yet formally outlined in the form of an explicit algorithm. This shows that ST1's computational thinking ability is at a medium level with high potential, especially in decomposition and algorithmic thinking. It is evidenced by the following interview excerpt.

R : *"How did you find the pattern/formula to solve the problem?"*
ST1 : *"From modification costs and cost savings."*
R : *"Explain!"*
ST1 : *"I saw in the problem that the car uses 10,000 liters of gasoline per year. Because the price of gasoline is 10,000 rupiah, so I just multiply it. One hundred million rupiah for the gasoline, ma'am."*
R : *"What other information did you add to solve the problem?"*
ST1 : *"Yes ma'am. First, I calculated the gasoline consumption per year, which is 10,000 liters. Because the price per liter is 10,000 rupiah, it means the total cost of gasoline is 100 million per year. I also added the annual maintenance cost of about 25 million. Finally, I divided the price of the car by its economic life, which is 150 million divided by 25 million per year, so the time needed is 6 years"*

This is in accordance with the results of research conducted by Danindra, 2020) which states that students who have good computational skills can determine the information needed, mention the steps of solving and solving problems precisely and quickly. Based on Figure 3, it can be seen that ST2 is able to break down the information into simpler components when trying to understand the problem. ST2 explained the given details, particularly those related to the amount spent on fuel, then determined the efficiency. This proves that ST2 started his thinking process by decomposing. Next, at the planning stage, ST2 did Although, ST2 can be said to have reached the pattern recognition stage in computational thinking. This is because ST2 was able to connect the problem with social arithmetic math material even though there were still errors.

R : *"What did you think when you first read the problem?"*
ST2 : *"First, I separated the different costs: fuel cost, modification cost, and total cost. I wrote everything down to make the components clear. Then, since the question asked how many years until break-even, I divided the total investment by the annual profit."*
R : *"Why did you divide it like that?"*
ST2 : *"Because the question was 'how many years to break even', so I figured it was total cost divided by annual savings. The steps are in order—kind of like an algorithm."*
R : *"How did you solve the part about the robots and puzzles?"*
ST2 : *"I grouped the items first. For example, in Option A, there are 2 robots, 3 puzzles, and 1 car. I added up the prices: 300 thousand plus 300 thousand plus 200 thousand, which makes 800 thousand. Then I calculated a 10% discount from 800 thousand and subtracted it, so it became Rp 720,000."*
R : *"And what about Option B?"*
ST2 : *"In Option B, I first calculated the discount for each item. Robots got 5%, puzzles 3%, and after summing them up, I subtracted another 15%. So it was done step by step, in order."*
R : *"You also wrote 'Get 18% discount' in Option C. Can you explain what you meant?"*
ST2 : *"Yes, the total spending in C is Rp 815,000. I first calculated a 10% discount, which gave Rp 733,950. But I also noticed that if you spend more than a certain amount, you get an additional 18% discount. I didn't calculate that yet, but I marked it because it's a general rule from the problem. I think that's part of abstraction—using a general rule."*
R : *"Did you compare all the options?"*
ST2 : *"Yes, I looked at the patterns. Option B, even though it includes more items, ends up being cheaper because it has bigger discounts. So I compared the pricing and discount patterns."*

ST2's difficulty in recognizing patterns affects subsequent stages of problem solving. Although ST2 demonstrates emerging signs of abstraction—such as attempting to filter relevant information—and shows a rudimentary sequence of steps resembling algorithmic thinking, these skills remain incomplete. ST2 does not successfully generalize the solution or articulate a clear conclusion, indicating that the abstraction indicator is not fully achieved. Likewise, the steps taken are neither logical nor systematic, showing that ST2 has not yet met the algorithmic thinking indicator at an adequate level.

ST2 showed CT ability which was also at a moderate level. ST2 was able to break down the problem into separate parts and organize the solution steps with a logical flow, although there were still corrections and lack of stability in the process. In recognizing patterns, ST2 used repeated calculation strategies but was not able to explain them explicitly. Abstraction is done intuitively by filtering out important information, but without generalization. The solution steps taken also showed a good basic algorithmic structure, although not yet formalized. ST2 still needs guidance in building explicit awareness of the strategies used.

As a developmental strategy, ST students need further challenges that can encourage them to be more explicit in expressing strategies and patterns, and improve thinking efficiency. It is recommended that teachers provide open-ended problems and modeling problems that encourage generalization, and engage students in visual representation activities such as flowcharts that can strengthen their algorithmic structure.

Medium SRL Student (SS)

The medium SRL subject (SS) showed moderate CT performance. Students SS1 and SS2 showed moderate and high mastery in CT indicators, with some strengths that need to be honed. On decomposition, they were able to explain the known and questioned information quite completely and correctly. SS2 was even able to describe the cost of each item in great detail. However, they still showed a tendency to repeat steps which made the solving process less efficient. In abstraction, they began to be able to identify important information, but sometimes still mixed up details that were not really needed in the solution process. In the pattern recognition indicator, their steps reflect regularity, but patterns are not consciously recognized or used as explicit strategies. In algorithmic thinking, they were able to construct logical steps and follow the flow of the solution, but could not explain the reasons why they chose that strategy.

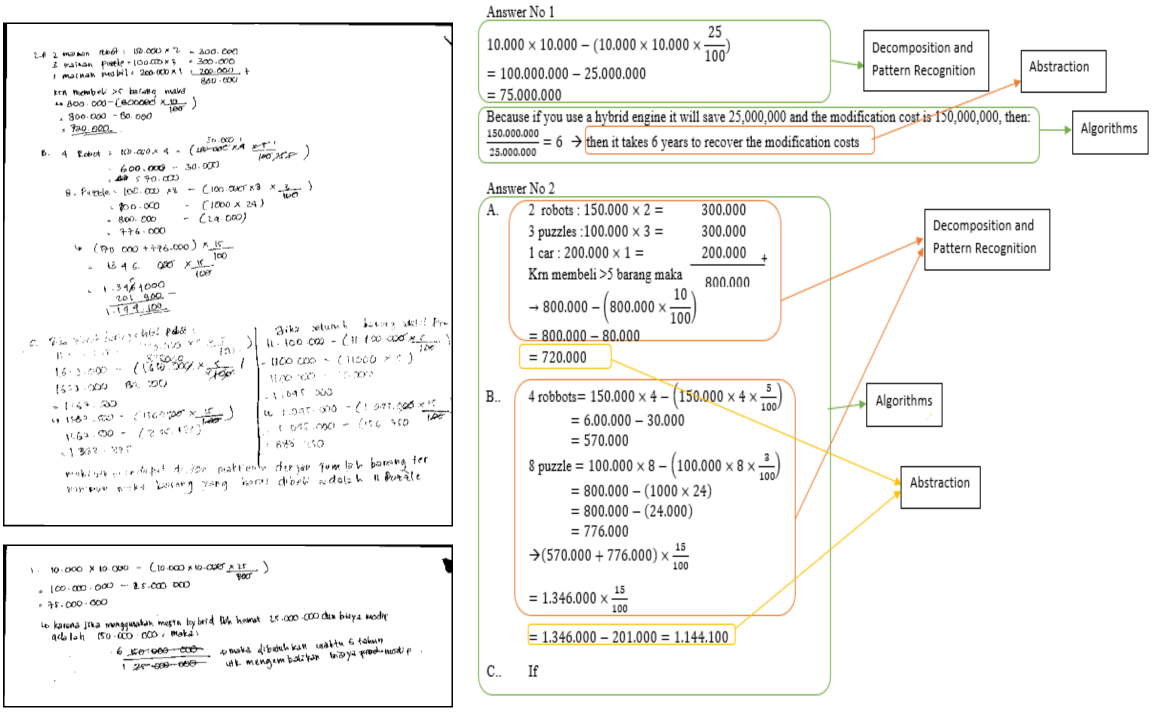

Figure 3. SS1 Answer Results

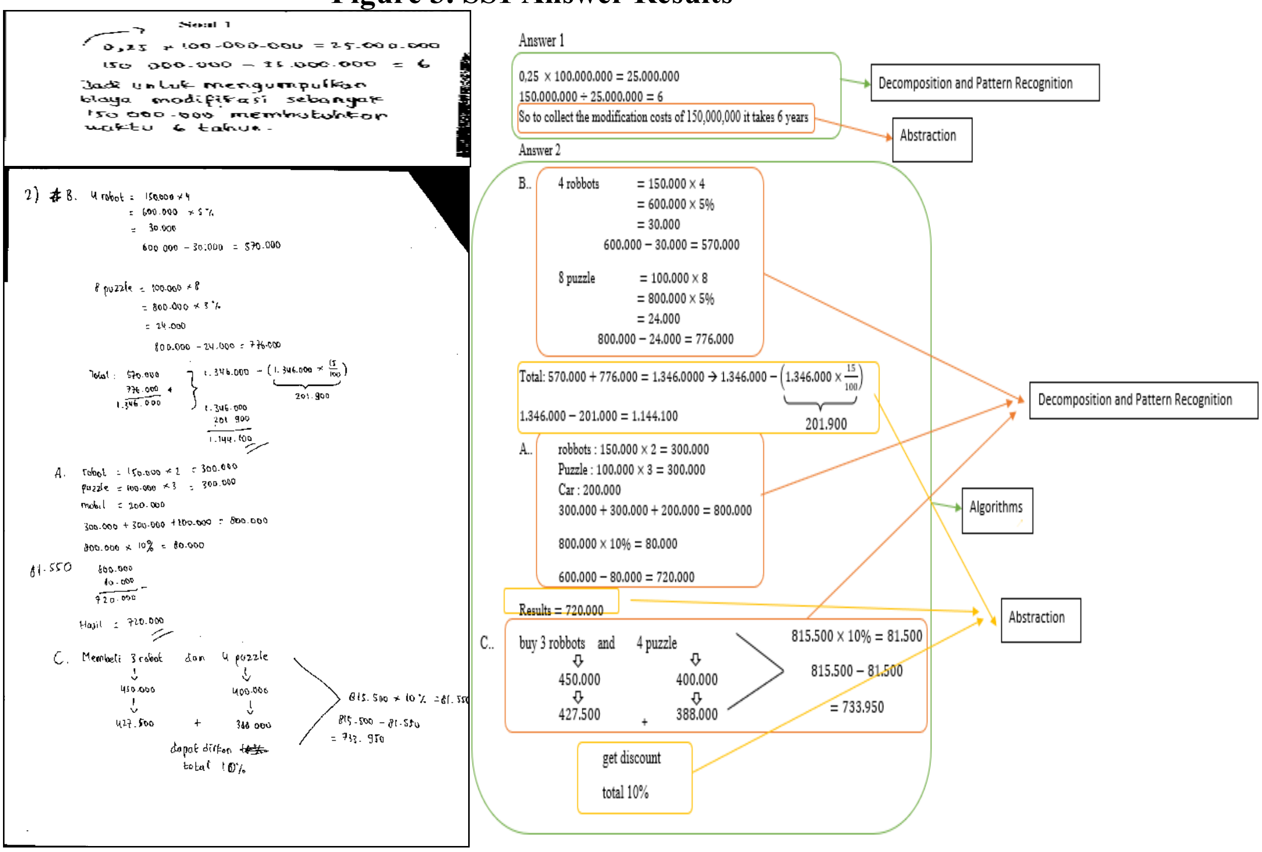

Figure 4. SS2 Answer Results

Student SS1 showed a good understanding of the problem structure in decomposition. He was able to divide the information and calculate part by part coherently. However, the pattern used in solving has not been recognized as a general strategy. His abstraction was quite good in focusing important information, but not yet efficient in the form of formal representation. In thinking algorithmically, SS1's steps were logical and sequential, but had not used a systematic format such as numbering. This reflects that SS1 has stable moderate CT ability, although it still requires training to improve strategy awareness and thinking process efficiency.

When approaching the hybrid engine problem, SS1 immediately identified the cost difference, which reflected abstraction of key numerical information: “Since the hybrid saves 25%, I subtracted 25% from 100 million, which gives 75 million.” The student then applied algorithmic thinking in deciding how to determine the break-even period: “It should be the modification cost divided by the savings per year.”

In solving the discount problem, SS1 demonstrated decomposition by breaking the task into smaller steps. For Option A, the student first summed the items and then applied the discount rule: “The total was 800 thousand rupiah… since there were more than five items, the 10% discount applied.” This indicated an ability to connect problem conditions with rules, showing pattern recognition. For Option B, SS1 calculated individual discounts per item before summing and applying the additional discount: “I applied those discounts before summing up the prices. Then I calculated an additional 15% discount from the total.” This sequential strategy highlighted algorithmic thinking, though the student admitted uncertainty about the correctness of the order: “I think the order is right, but I’m not sure if the final result is really the cheapest.” Finally, when asked about Option C, SS1 acknowledged incomplete work due to time constraints: “I didn’t have time to fully calculate Option C… I finished the parts I was most confident about.” This illustrates both the student's reliance on partial decomposition and the limits of their strategic regulation in problem-solving.

Interestingly, SS2, with the highest score of 92.86 and also an Olympiad student, showed high CT ability. SS2 was able to perform decomposition very well, organizing calculations per item clearly and systematically. In pattern recognition, although not yet fully explicit, SS2 showed consistency in following the solution structure. He also showed quite mature abstraction ability by ignoring irrelevant information and focusing on important quantitative data. In algorithmic thinking, SS2 organized the sequence of solution steps with a logical and systematic structure. Although not yet using an explicit algorithmic format, his flow of thinking was very strong. SS2 only needs encouragement to express the strategy explicitly to optimize his ability. It is in accordance with research by Kamil (2021) which suggests that students in the moderate category have been able to mention important information and mention the steps of solving and solving problems correctly.

When solving the toy purchase problem, SS2 began by separating the calculation for each item, which indicated decomposition: *"I counted them one by one: robot, car, and puzzle."* The student then applied pattern recognition by noticing that the discount procedure was the same for each product: *"20% discount means price × 20%, then subtract from the price."* After reflection, the student recognized the possibility of generalizing this into a formula (*final price = initial price × (100% discount%)*), demonstrating abstraction. Finally, SS2 organized the steps sequentially calculating subtotals before summing them revealing algorithmic thinking.

This progression shows how the student's problem-solving strategy naturally engaged all four CT indicators, though initially performed intuitively rather than through explicit formula use. With teacher scaffolding, the student became more aware of the underlying CT processes, particularly the advantages of abstraction and algorithmic organization in simplifying and systematizing the solution.

To strengthen students' abilities in this category, learning strategies include structured and explicit reflective exercises, such as asking students to explain the reasons behind their solution steps (self-explanation) to increase awareness of the patterns used. Explicit pattern recognition can be done through problems with similar structures to help them generalize their solution strategies. In addition, the use of visual representations such as flowcharts, step tables, or simple pseudocode is important to strengthen algorithmic understanding and help students organize solution steps systematically. For strengthening abstraction, teachers can provide guiding questions and open-ended problem exercises that encourage students to develop a generalized form of the solution found. Especially for students like SS2 who have high CT ability, learning strategies can also include contextual mini-projects and group discussions or peer teaching so that they can express their thinking strategies explicitly and reflectively, while assisting peers in developing a deeper understanding of the patterns and logic of problem solving.

Low SRL Student (SR)

SR1 and SR2 showed considerable challenges in mastering CT skills. SR1's characteristic of giving up easily showed a moderate level of CT skills, but not yet stable. In decomposition, he was able to divide the problem into smaller parts, but there were still incompletenesses. He used repeated calculation patterns, but did not realize or explicitly state the patterns. Abstraction is done at an early level, where important information can be filtered but not yet converted into an efficient form. SR1's algorithmic thinking was systematic, but immature in structure and strategy. This student shows basic potential in CT, but requires explicit and reflective learning to develop stronger thinking strategies.

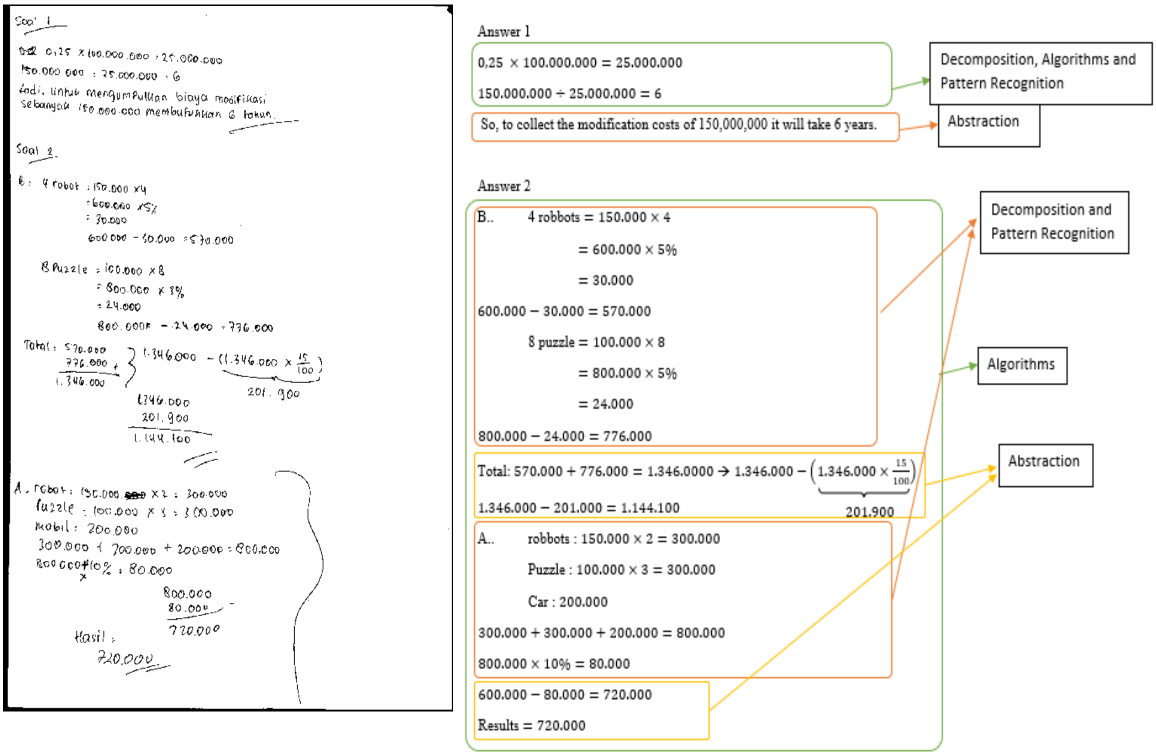

Figure 5. SR1 Results Answer

Figure 5 presents the written response of student SR1, who was categorized as having low self-regulated learning (SRL) and moderate computational thinking (CT) skills. The answer demonstrates SR1's attempt to solve two PISA-like mathematics problems involving multi-step calculations and discount reasoning. To gain deeper insight into the student's problem-solving approach, a think-aloud session and follow-up interview were conducted. The following transcript captures SR1's explanation and reasoning while working through the tasks.

When solving the hybrid engine problem, SR1 immediately focused on the numerical values and directly calculated the annual savings: *"I multiplied 0.25 by 100 million… then I divided 150 million by 25 million and got 6."* This shows the use of abstraction to identify relevant information, but also a reliance on memorized procedures rather than reflective reasoning: *"I didn't really think it through I just followed the formula I remembered."*

In the discount problem, SR1 demonstrated decomposition by calculating subtotals for each product before applying discounts. For instance, the student explained: *"I first multiplied 150,000 by 4… then subtracted 5%… I did the same with the puzzles… then I added them up and applied a 15% discount."* The process was sequential, showing elements of algorithmic thinking, but the student relied heavily on calculators: *"I just tried 15% of 1,346,000… I didn't use a detailed method just used a calculator."*

For Option A, SR1 again decomposed the task by summing all items before applying the discount rule: *"The total was 800,000. Since I bought more than five items, I subtracted 10%."* This reflected pattern recognition, as the student connected the discount condition with the number of items purchased. However, when comparing results, SR1 admitted limited evaluation: *"I wrote down both, but I didn't really think about which one was cheaper."* This indicates weak metacognitive regulation in verifying the efficiency of strategies.

Overall, SR1's responses showed partial mastery of CT indicators clear decomposition and basic algorithmic steps, but limited abstraction and pattern generalization. The lack of planning and reflection, as expressed by the student (*"I just did whichever part I could first"*), further revealed difficulties in systematically organizing and evaluating problem-solving strategies.

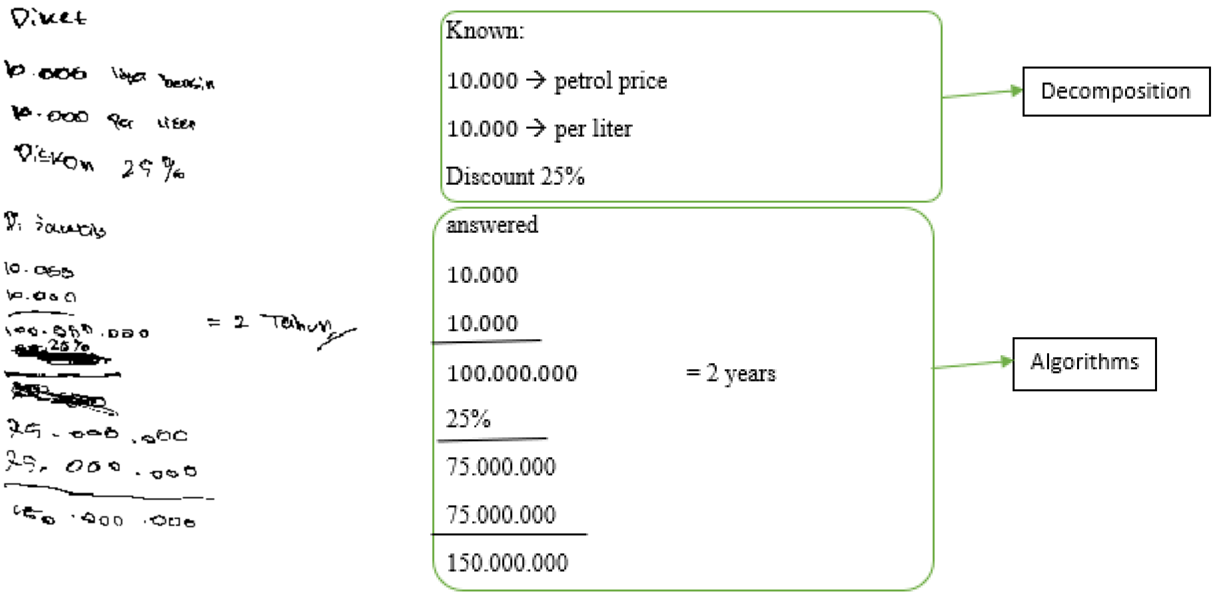

Figure 6. SR2 Answer

In contrast, subject SR2 on figure 6, with a score of 50 and characteristics of restlessness and giving up easily, showed low CT ability. She had difficulty in all CT indicators. In decomposition, there was no clear separation of the problem structure, and the solution steps appeared random. There was no consistent pattern recognition, and abstraction was underdeveloped as the student failed to sort out relevant information. Algorithmic thinking had also not emerged, as the steps written were not logical or systematic. This condition shows that SR2 needs a highly structured learning approach, intensive support, and gradual practice in recognizing patterns, strategizing, and reflecting on the problem solving process. This is consistent with the following interview excerpt.

In problem 1, SR2 showed initial effort in identifying relevant quantities but lacked confidence to proceed: *"I first calculated the total liters of gasoline… then I multiplied it by the price. But after that there are other costs, I'm confused whether to add them first or divide them first."* This reflects a partial attempt at decomposition, but the student's uncertainty about the sequence revealed weaknesses in algorithmic thinking. The hesitation eventually led to abandoning the solution: *"I was afraid of being wrong, so I didn't continue."*

In problem 2, SR2 did not attempt a written solution, admitting difficulty in handling multiple discount conditions: *"The discounts were different, so I got dizzy. I thought it was harder than the first problem, so I just skipped it."* This illustrates limited pattern recognition, as the student could not generalize or connect discount procedures across items. Furthermore, the statement *"I forgot the formula. So I don't know where to start"* indicates insufficient abstraction, since the student failed to recall or construct a general representation of the discount rule.

Overall, SR2's responses show low engagement with CT indicators. While some decomposition was evident, weaknesses in abstraction, pattern recognition, and algorithmic organization hindered progress. The student's reluctance to continue also highlights motivational and self-regulation challenges, which further constrained the application of CT in problem-solving.

To support the development of SR students, a structured, purposeful and nurturing learning approach is needed. Teachers are advised to use *worked examples* or complete sample problems as an initial reference for students, accompanied by a step-by-step guide in the form of simple guiding questions to help them organize their thinking process gradually. Repetitive, fixed-pattern exercises are essential to build the habit of recognizing patterns and devising solution strategies. In addition, visual representations such as tables, flowcharts, or concept maps can make it easier for students to organize information. Simple guided reflections after problem solving are also necessary to practice conscious thinking (metacognition), although they should be done with direct guidance. Prompt and positive feedback is needed so that students understand the process as a whole, not just the final result. In addition, teachers also need to provide affective support, create a safe learning atmosphere and motivate students through appreciation of effort, in order to build confidence and enthusiasm for learning in a sustainable manner.

Table 5. Comparison of Computational Thinking Ability in ST, SS, and SR Subjects

CT Indicator	ST (High SRL)	SS (Medium SLR)	SR (Low SRL)
Abstraction and Generalization	ST was able to identify key elements and formulate general patterns from the problem information. In addition, ST attempted to apply efficient problem-solving strategies, although minor inaccuracies were found in the final generalization.	SS was able to mention general formulas or strategies in some questions but did not consistently connect them to the overall context of the problem.	SR showed no evidence of generalization. The student focused only on numerical data without deriving meaning or identifying patterns from the problem.
Decomposition	ST successfully decomposed the problem by clearly identifying and explaining both known and unknown elements.	SS was able to identify and explain what was known and what was asked in the problem completely and accurately.	SR provided only partial information. Several key components were not addressed, and there were misunderstandings in interpreting the problem.
Pattern Recognition	ST effectively recognized patterns necessary to solve the problem accurately and in a structured manner.	SS was able to identify patterns but could not explain the reasoning behind their use or the relationships between problem elements accurately.	SR was unable to explain any patterns and failed to understand the relationships between elements in the problem.
Algorithmic Thinking	ST described and justified logical step-by-step procedures to reach the correct solution.	SS outlined logical steps to solve the problem in a reasonably coherent order, but inconsistencies were found in the final execution.	SR attempted to describe solution steps, but significant errors were observed in logic and application.

Discussion

The results of this study suggest that self-regulated learning is strongly related to the quality of students' computational thinking, particularly in solving PISA-like mathematical problems. Students with high SRL demonstrate better strategic planning, flexible problem-solving, and reflection, which align with Grover and Pea (2013) computational thinking framework.

Students in the high SRL group (ST) performed better across all CT indicators, especially in abstracting and algorithmic thinking. They were capable of planning their problem-solving, monitoring their progress, and reflecting on the appropriateness of strategies hallmarks of both SRL and effective CT.

In contrast, students with medium SRL (SS) showed potential but lacked depth in explanation and generalization. While they were able to complete tasks and follow procedures, they often failed to explain why certain strategies were used suggesting a gap between procedural fluency and conceptual understanding.

The low SRL student (SR) struggled to manage problem complexity and lacked reflective ability, which impacted all CT indicators. This supports previous findings that SRL contributes not only to motivation but also to metacognitive control, both essential in tackling open-ended mathematical tasks.

These results suggest that strengthening students SLR should be a priority in Indonesian classrooms, especially in the context of the Merdeka Curriculum's emphasis on higher-order thinking and the ongoing need to improve students' performance on PISA tasks that demand strong computational thinking skills (Supiarmo, M. Gunawan & Tarmuzi, 2022). Integrating structured opportunities for planning, monitoring, and reflecting within math instruction could help students improve both self-regulation and computational problem-solving (Song et al., 2021).

Moreover, the findings align with OECD PISA goals, which emphasize not just content mastery but also reasoning, problem-solving, and adaptability in novel contexts. The poor performance of low SRL students in this study is consistent with international and national reports indicating that many Indonesian students struggle with PISA-type mathematics tasks requiring multistep logical reasoning (OECD, 2023) .

When comparing students across SRL levels, a clear gradient in computational thinking (CT) proficiency emerges. High-SRL students consistently demonstrated the strongest CT performance, marked by effective decomposition of complex problems, consistent pattern recognition, meaningful abstraction, and logically sequenced algorithmic steps. Their ability to plan, monitor, and reflect on their thinking allowed for more strategic and adaptive responses to PISA-like problems. In contrast, medium-SRL students showed partial mastery: they were generally able to decompose problems and follow logical steps but struggled with articulating patterns or generalizing strategies, reflecting gaps in metacognitive control. Low-SRL students exhibited the weakest CT capabilities, often failing to initiate structured approaches, with frequent cognitive disorientation and minimal evidence of abstraction or algorithmic thinking. This progression suggests that SRL not only supports motivational and behavioral regulation but also enhances higher-order cognitive functioning necessary for CT (Kong & Wang, 2024; Pasterk & Benke, 2024). The findings underscore the interdependence between self-regulatory mechanisms and students' capacity to engage in sophisticated mathematical reasoning, particularly in complex, real-world problem contexts.

CONCLUSION

This study suggests that SRL is closely associated with the quality of students computational thinking when working on PISA-like mathematical problems. Students with higher SRL levels generally showed stronger performance across the four CT dimensions, decomposition, pattern recognition, abstraction, and algorithmic thinking, although not without occasional inaccuracies. Their responses indicate a greater tendency to approach problems in a structured, reflective, and strategic manner, enabling them to break down complex tasks, identify relevant patterns, make preliminary generalizations, and develop more coherent solution steps compared to their peers.

Students with moderate SRL showed partial mastery, especially in decomposition and algorithmic steps, but often lacked efficiency and clarity in recognizing patterns and abstracting general principles. In contrast, students with low SRL exhibited significant cognitive and motivational difficulties, often failing to initiate coherent strategies or complete problem-solving steps systematically.

These findings suggest a close relationship between students metacognitive regulation (SRL) and their ability to apply computational thinking skills in real-world mathematical contexts. SRL enhances the autonomy and self-awareness necessary for CT development, while CT provides a structured pathway for students to execute self-directed problem-solving processes. This synergy is essential in preparing learners for 21st-century demands, especially in educational systems that emphasize mathematical literacy, digital competencies, and adaptive reasoning, such as those assessed by PISA.

Therefore, mathematics instruction should move beyond content delivery and intentionally integrate SRL and CT development through reflective learning tasks, problem decomposition exercises, pattern-based challenges, abstraction modeling, and algorithm design. Teachers are encouraged to design classroom routines that incorporate goal-setting, progress monitoring, and self-reflection activities, while providing gradual scaffolding to transfer responsibility to students. In practice, this can be realized through learning journals, collaborative problem-solving, or digital tools that guide students to monitor and evaluate their strategies. For policymakers, these findings suggest the value of integrating SRL and CT more explicitly into mathematics curricula, offering professional development that supports metacognitive and computational thinking pedagogy, and providing resources that enable technology enhanced learning environments conducive to fostering both SRL and CT.

Future research should explore the implementation of structured SRL–CT learning models across various mathematical domains and grade levels, investigate longitudinal effects on student performance, and examine the scalability of digital interventions that combine SRL training with CT-rich learning environments.

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