Jurnal Elemen, 11(4), 996-1017, October 2025
https:/doi.org/10.29408/jel.v11i4.32082

e- ISSN: 2442 - 4226

Check for updates

How mathematical disposition shapes computational thinking in solving systems of linear equations: A flowchart-supported qualitative study

Ananda Jullailatul Azizia [1], Masrukan [1 *], Bambang Eko Susilo [1], Ahmad Arifuddin [2]

[1] Universitas Negeri Semarang, Central Java, Indonesia

[2] Universitas Islam Negeri Siber Syekh Nurjati Cirebon, West Java, Indonesia

[*] Correspondence: masrukan.mat@mail.unnes.ac.id

Abstract

Computational thinking (CT) is a vital 21st-century skill in mathematics education, enabling students to solve problems systematically through decomposition, pattern recognition, abstraction, and algorithmic thinking. However, students' mathematical disposition—encompassing beliefs, habits of mind, and affective tendencies—may significantly influence CT development. Guided by the affective–cognitive interaction model, this study aimed to explore how mathematical disposition shapes students' CT skills, particularly in solving systems of three-variable linear equations using self-constructed, flowchart-supported algorithmic representations. A descriptive qualitative approach was adopted, with six students (two each from high, medium, and low disposition levels, identified via questionnaire) participating. Data collection involved a disposition scale, CT test, interviews, and documentation. Findings revealed that high-disposition students successfully demonstrated all CT indicators and produced coherent flowcharts. Medium-disposition students showed variability: some met all criteria, while others faltered in algorithmic design. Low-disposition students managed only basic decomposition and pattern recognition, with incomplete abstraction and fragmented flowcharts. These results suggest a strong link between affective factors and cognitive performance in CT tasks. Implications highlight the importance of integrating disposition-aware scaffolding—such as interactive visual tools and guided reflection—to support diverse learners and enhance CT development in mathematics classrooms.

Keywords: computational thinking skills; flowchart-supported; mathematical disposition

How to cite: Azizia, A. J., Masrukan, Susilo, B. E., & Arifuddin, A. (2025). How mathematical disposition shapes computational thinking in solving systems of linear equations: A flowchart-supported qualitative study. *Jurnal Elemen, 11*(4), 996-1017. https://doi.org/10.29408/jel.v11i4.32082

Received: 15 August 2025 | Revised: 5 October 2025
Accepted: 11 October 2025 | Published: 9 November 2025

Introduction

Computational thinking is one of the essential skills in the 21st century and supports the challenges of the Industrial Revolution 4.0 era (Ramaila & Shilenge, 2023; Suarsana et al., 2024). Computational thinking is highly necessary for developing critical thinking, fostering creativity, and enhancing problem-solving abilities (Nordby et al., 2022). It is a way of understanding and solving complex problems using techniques and concepts from computer science, involving decomposition, pattern recognition, abstraction, and algorithms (Lee et al., 2023; Muhammad et al., 2023; Supiarmo et al., 2022). Computational thinking is not only about solving problems but also about reasoning through problems, formulating questions, and estimating possible solutions (Maharani et al., 2019). It is recognized as a basic cognitive problem-solving procedure that facilitates modern literacy (Doleck et al., 2017). Through computational thinking, individuals can easily observe problems, search for solutions, solve problems, and develop effective problem-solving strategies. Moreover, computational thinking trains individuals to think more effectively and efficiently. Therefore, it is crucial for students to possess strong computational thinking skills.

Computational thinking involves a process of logical reasoning, which includes algorithmic thinking, problem decomposition, pattern recognition and generalization, abstraction, and evaluation to solve and understand complex problems more easily (Angeli, 2022; Tang & Ma, 2023; Wing, 2017). According to Isharyadi and Juandi (2023), computational thinking consists of decomposition, pattern recognition, abstraction, and algorithmic thinking. The characteristics of computational thinking, according to Sezer and Namukasa (2023), are as follows: 1) decomposition: students can identify the required information or what is known from a given problem, as well as identify what is being asked based on the information provided; 2) pattern recognition: students can understand existing patterns and relate them to previously learned patterns; 3) abstraction: students can draw conclusions by eliminating unnecessary elements when implementing a problem-solving plan, and 4) algorithmic thinking: students can describe the logical steps used to construct a solution to the given problem. Thus, mastering computational thinking skills helps in recognizing patterns and deepening the understanding of problems to be solved.

A preliminary study conducted in class X-11 at MAN 1 Kota Semarang involving 35 students aimed to measure their computational thinking skills. The findings revealed that students were able to identify known and asked-for information in a problem and could determine a problem-solving strategy using the formula $U_n = a + (n-1)b$. However, they were unable to transform real-life problems into mathematical problems and could not solve them using logical step-by-step reasoning. This aligns with the computational thinking indicators, showing that students had not met the abstraction and algorithmic thinking criteria—where abstraction requires the ability to eliminate irrelevant elements when executing a solution plan, and algorithmic thinking requires the ability to outline logical steps for solving a problem. Therefore, based on the results of this preliminary test, it is evident that students have not yet optimally utilized computational thinking skills, highlighting the need for improvement in this area.

These findings were reinforced by interviews conducted at MAN 1 Kota Semarang, which revealed that while learning was intended to be student-centered, students were not actively engaged in the learning process. Although teachers sometimes provided word problems, many students still struggled to solve mathematical problems in the form of real-life story questions. This difficulty arose because students often had trouble understanding the problems, making it hard for them to focus on the core issues. Furthermore, they struggled to connect relevant concepts needed to solve problems, which hindered their ability to plan and determine effective solution steps (Wang, 2023). Consequently, students still required guidance from teachers to find solutions to word problems. This situation reveals a gap compared to previous studies, which found that mathematical computational thinking skills remain limited to the algorithmic indicator and have yet to reach a satisfactory level. In particular, students have not been able to solve mathematical problems by writing down more effective and simplified solution steps. Indicators of mathematical computational thinking that tend to be weaker include decomposition, abstraction, and algorithmic thinking (Isharyadi & Juandi, 2023; Sezer & Namukasa, 2023).

One effective tool for applying algorithmic thinking steps in computational thinking is the flowchart, which visualizes the problem-solving process in an ordered instructional diagram. Using flowcharts helps students better understand the logical sequence of problem-solving steps in a more systematic and structured manner (Threekunprapa & Yasri, 2020; Zhang et al., 2023). Additionally, Rahman et al. (2020), found that flowcharts can enhance students' computational thinking skills by enabling them to visualize algorithms before implementing them in programs or manual solutions. Thus, the use of flowcharts not only supports the systematic design of algorithms but also strengthens computational thinking skills in various learning contexts and real-world educational media development.

In this study, the flowchart is utilized as a mediating learning tool aimed at enhancing students' algorithmic thinking skills, which constitute one of the key dimensions of computational thinking. Through the implementation of flowcharts, students are guided to represent the logical sequence of steps in solving mathematical problems systematically, enabling them to visualize thought processes, recognize interprocess relationships, and evaluate the effectiveness of the strategies employed. Explicit instruction on the use of flowcharts is provided through learning activities involving the identification of symbols, analysis of decision branches, and reflection on the constructed logical flow. Thus, the flowchart functions not only as a visual aid but also as a cognitive and affective mediation mechanism that bridges algorithmic thinking processes with students' mathematical dispositions, particularly in fostering self-confidence, perseverance, and independent logical reasoning in problem solving.

Computational thinking (CT) is inherently connected to real-world problem solving and is strongly influenced by students' affective mastery, particularly their mathematical disposition (Begum et al., 2021; Jong et al., 2020). According to NCTM (2000), mathematical disposition as a constellation of beliefs, habits of mind, and affective tendencies. involves confidence, curiosity, perseverance, and appreciation of mathematics in daily life factors that support holistic cognitive affective development (Azizia et al., 2024). The affective–cognitive interaction model Zan et al. (2006), explains that perseverance and self-confidence facilitate algorithmic thinking and abstraction, while Self-Determination Theory (Ryan & Deci, 2000), highlights that competence and autonomy enhance intrinsic motivation for CT engagement. Empirical studies confirm this interrelation: reflective and critical dispositions strengthen cognitive flexibility that supports algorithmic reasoning (Jong et al., 2020; Pérez, 2018).

Recent findings further emphasize this link, showing that students' beliefs and attitudes toward mathematics significantly shape their computational competencies (Zhang et al., 2023). Integrating CT into the curriculum fosters not only abstraction and algorithmic thinking but also reflective engagement and positive attitudes (Lee et al., 2023). CT itself consists of four interrelated dimensions decomposition, pattern recognition, abstraction, and algorithmic thinking each requiring affective traits such as perseverance, curiosity, flexibility, and confidence (Mertens & Colunga, 2025). Thus, CT and mathematical disposition form a mutually reinforcing framework: cognitively, CT structures systematic reasoning and enhances students' confidence (Lee et al., 2023; Mertens & Colunga, 2025); affectively, disposition nurtures motivation and willingness to engage in computational problem-solving (Lee et al., 2023; Zhang et al., 2023). A strong disposition fosters perseverance and appreciation for the problem-solving process itself. Consequently, interventions to strengthen CT should also cultivate positive mathematical dispositions, ensuring that cognitive and affective growth develop synergistically within a reflective and meaningful learning environment (Lee et al., 2023).

Several prior studies have investigated computational thinking in mathematics learning (Calao et al., 2015; Elicer et al., 2023; Sezer & Namukasa, 2023; Solitro et al., 2017; Wardani et al., 2022). Some researchers have examined it from the perspectives of self-efficacy (Azizia et al., 2023; Kayhan et al., 2024), self-confidence (Firmasari et al., 2025; Psycharis & Kotzampasaki, 2019), and self-regulated learning (Hariyani et al., 2024). However, research specifically exploring how mathematical disposition influences students' computational thinking processes remains limited. Likewise, few studies have presented visual representations in the form of flowcharts to model students' thinking processes systematically (Chinofunga et al., 2025; Cromley & Chen, 2024; Schraw & Richmond, 2022).The use of flowcharts in computational thinking is theoretically grounded in their ability to externalize algorithmic structures, transforming abstract reasoning into concrete visual forms. They also foster metacognition by allowing learners to monitor and refine their thought processes, consistent with dual-coding theory, which emphasizes that combining verbal and visual representations enhances learning and retention (Clark & Paivio, 1991; Fleur et al., 2021). Therefore, this study aims to analyze students' computational thinking processes based on their mathematical disposition levels using flowchart visual representations. This visualization is expected to describe students' thought processes in detail, distinguish problem-solving strategies across disposition categories, and contribute to designing adaptive, responsive mathematics learning tailored to students' characteristics.

Methods

This study employed a qualitative approach with an exploratory descriptive design, which aimed to analyze students' computational thinking skills in relation to their mathematical dispositions through the completion of mathematics problems assisted by flowcharts. A qualitative approach was chosen as it allowed the researcher to explore in depth the students' thinking processes and problem-solving strategies within the context of real classroom learning (Silverman, 2021).

The research subjects were six students from class X-5 of MAN 1 Kota Semarang, who had previously studied the topic Systems of Three-Variable Linear Equations. The subjects were selected purposively based on the category of mathematical disposition level (high, medium, low) obtained through a questionnaire. This selection was made to obtain in-depth data variation in the context of the case study, with the awareness that the results of this study are analytical generalizations and have limitations in statistical generalization. Mathematical disposition was defined as a constellation of beliefs, habits of mind, and affective tendencies (Kusmaryono et al., 2019; NCTM, 2000).

The instruments used in this study consisted of: (1) a mathematical disposition questionnaire to classify students into three disposition levels, adapted from Arifuddin (2024) all items in the mathematical disposition questionnaire have r-count values greater than r-table (0.388), indicating that the instrument is valid. Furthermore, the Cronbach's Alpha value of 0.935 demonstrates very high reliability, confirming that the questionnaire is suitable for use as a research instrument; (2) computational thinking skill test items; (3) interview guidelines; and (4) observation sheets and documentation of students' work.

Table 1. Question indicator computational thinking

Learning Objective	Question Indicator	Computational Thinking Skill Indicators	Item Number
Solve contextual problems related to systems of three-variable linear equations	Given a word problem about purchasing food and drinks at KFC with package prices, students can calculate the price of each type of food and drink using the solution method.	1. Decomposition 2. Pattern Recognition 3. Abstraction 4. Algorithmic Thinking	1
	Given a word problem about purchasing stationery at two different stores, each offering different package prices, students can determine which store is more recommended between the two.		2

All instruments were validated through expert assessment involving two mathematics education lecturers and one mathematics teacher who assessed their content and structure. Revisions were made based on their feedback to ensure alignment with the research objectives. The instrument trial was conducted with Class XI-1 students at MAN 1 Kota Semarang, consisting of four test items. The results indicated that all items were valid, as the calculated correlation coefficient $r_{count} > r_{table}(0.329)$. The reliability coefficient of the test was $r_{11} = 0.7367$, categorized as high, demonstrating good internal consistency of the instrument. The difficulty levels ranged from moderate to difficult, while the discrimination indices for all items were classified as very good. These findings confirm that the instrument is valid, reliable, and appropriate for assessing students' computational thinking abilities.

The research procedure was conducted in the following stages:

1. Preparation Stage
   a. Development of the computational thinking skill instrument, validated by subject-matter experts.
   b. Pilot testing of the instrument to ensure clarity and appropriateness of test items.
   c. This study received ethical approval from the Research Ethics Committee of Semarang state university and obtained ethical approval from the relevant institutional ethics committee. As the participants were minors, parental consent and student assent were obtained prior to conducting the study. Participation was voluntary, and students were informed of their right to withdraw at any time without consequences. All personal data was anonymized to maintain confidentiality.
   d. In the learning process, flowcharts are introduced as visual aids (visual scaffolding) to help students externalize and organize their algorithmic thinking patterns in a more structured manner. At the beginning of the activity, students are given a brief introduction to the basic conventions of using flowcharts, such as the use of process symbols, decision symbols, and arrows to indicate the flow. After the introductory stage, students carry out computational problem-solving tasks, where they are given the freedom to use or not use flowcharts in representing their thought processes. This design aims to observe the extent to which visual representation through flowcharts can facilitate or differ from non-visual thinking in developing algorithmic problem-solving strategies.
   e. The research was conducted after instruction on the topic system of three variable linear equations, followed by the administration of the Computational Thinking (CT) test to measure students' algorithmic thinking skills. Students were given 60 minutes to complete the test.
2. Data Collection Stage
   a. Administration of the mathematical disposition questionnaire to all 36 participants. In this study, the mean (μ) and standard deviation (σ) were used as the basis for determining students' mathematical disposition categories, since each class exhibited different score distributions. Therefore, the μ ± σ approach was considered the most appropriate to provide a fair, representative, and context-sensitive classification according to each class's characteristics. This method allows the researcher to illustrate students' ability variations proportionally while preserving the natural variability of the data within each group. Based on the calculated mean and standard deviation values, the categorization of students' mathematical disposition scores is presented in the following table.

Table 2. Mathematical disposition categories for Class X-5

Score Range	Mathematical Disposition Score	Category
$X \geq \mu + \sigma$	$X \geq 91.35$	High
$\mu - \sigma \leq X < \mu + \sigma$	$68.82 \leq X < 91.35$	Medium
$X < \mu - \sigma$	$X < 68.82$	Low

b. Administration of the computational thinking test, which measured four indicators decomposition, pattern recognition, abstraction, and algorithmic thinking based on the indicators listed in Table 1. The test used contextual problems in the form of a system of three-variable linear equations along with a task requiring students to create a flowchart.
c. Selection of six students (two from each disposition category) for semi-structured interviews. The interviews explored problem-solving strategies, use of flowcharts, pattern recognition, abstraction processes, and error correction.

3. Data Analysis Stage
   a) Analysis of mathematical disposition questionnaire scores using the categorization formula in Table 2 to determine each student's disposition level.
   b) Analysis of computational thinking test results using a rubric aligned with the four indicators (decomposition, pattern recognition, abstraction, algorithmic thinking), focusing on accuracy, completeness, and systematic representation.
   c) Analysis of interview transcripts following Huberman's model:
      1) Data reduction selecting relevant excerpts and coding key themes related to computational thinking processes.
      2) Data display organizing findings in tables, flowcharts, or descriptive profiles for each subject.
      3) Conclusion drawing and verification identifying patterns, linking computational thinking performance with mathematical disposition, and checking consistency across test, questionnaire, and interview data.

Results

Results of students' computational thinking and mathematical disposition

The following are the results of students' computational thinking skills and mathematical dispositions, which were categorized into high, medium, and low levels.

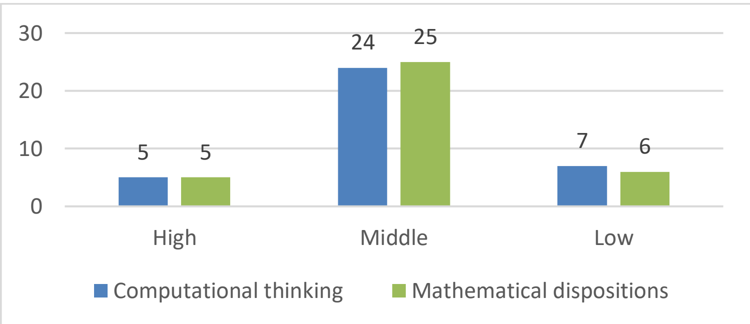


Figure 1. Categori computational thinking and mathematical dispositions

For a more in-depth analysis, six research subjects were selected, each representing different categories. The selection of these subjects aimed to illustrate the variations in students' characteristics when solving flowchart-based problems. The following table presents the selected subjects.

Table 3. Six research subjects

Number	Students Code	Mathematical dispositions		Computational thinking	
1	E35	High	112	High	100
2	E12	High	105	High	91,67
3	E31	Middle	81	Middle	83,33
4	E29	Middle	76	Middle	70,83
5	E32	Low	68	Middle	62,50
6	E36	Low	67	Low	58,33

Based on Table 3, overall, higher mathematical disposition tends to align with higher computational thinking (CT) performance. However, participant E32 represents a notable exception despite low disposition, achieved medium CT due to scaffolding during problem solving. This suggests that instructional support can enhance CT performance even among learners with low disposition.

The results of the computational thinking skills test taken by class X-5 students, along with interview data, were used as a reference to classify students according to the indicators of computational thinking skills. The test results and interview data were examined with reference to the four indicators of computational thinking: decomposition, pattern recognition, abstraction, and algorithmic thinking.

Students' computational thinking skills with high mathematical disposition

The mathematical disposition of students in the high category toward computational thinking skills was described based on the test results and interview data from two subjects, namely E35 and E12.

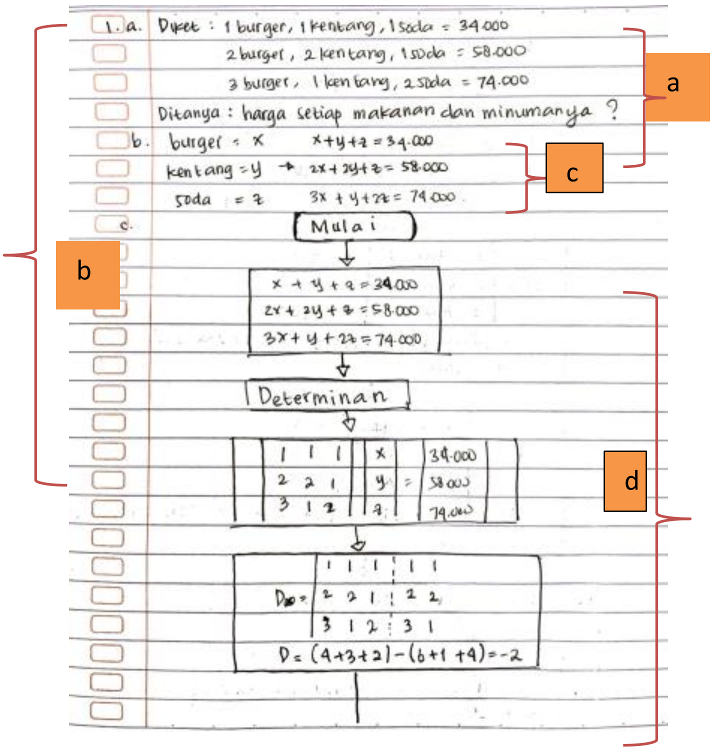
Subject E35, with a mathematical disposition score of 112 (high category), obtained a post-test score of 100, which was classified as high-level computational thinking skills. The following is the result of the post-test. Subject E35 was able to answer question number 1 correctly.

Subject E35 correctly answered the question by writing down the important information provided in the problem:

"Given: 1 burger, 1 fries, and 1 soda = Rp 34,000; 2 burgers, 2 fries, and 1 soda = Rp 58,000; 3 burgers, 1 fries, and 2 sodas = Rp 74,000. Asked: the price of each type of food and drink."

Based on the test results and interview data, subject E35 demonstrated strong ability in identifying the given information in detail and accurately understanding the information being asked. This indicates that the subject had successfully achieved the decomposition indicator, namely the ability to break down complex problems into simpler and more relevant pieces of information. The subject's ability in pattern recognition and abstraction was also evident from their skill in recognizing the relationships among variables in the problem.. The subject independently organized the information into a system of three-variable linear equations and was able to identify the correlation between the quantity of items and their total price:

"Let x = burger, y = fries, and z = soda. The mathematical model is: x + y + z = 34,000; 2x + 2y + z = 58,000; 3x + y + 2z = 74,000. Then I used the determinant method."



a. Decomposition: The student successfully breaks down the contextual problem into three main components (burger, fries, soda) and represents them in a system of linear equations.
b. Pattern Recognition: The student identifies structural similarities among the equations and recognizes coefficient patterns to select the appropriate solving method.
c. Abstraction: The student simplifies the real-world problem into a symbolic mathematical model (x, y, z) that is relevant and easy to analyze.
d. Algorithmic Thinking: The student organizes logical steps in a flowchart, showing procedural order from problem identification to determinant calculation

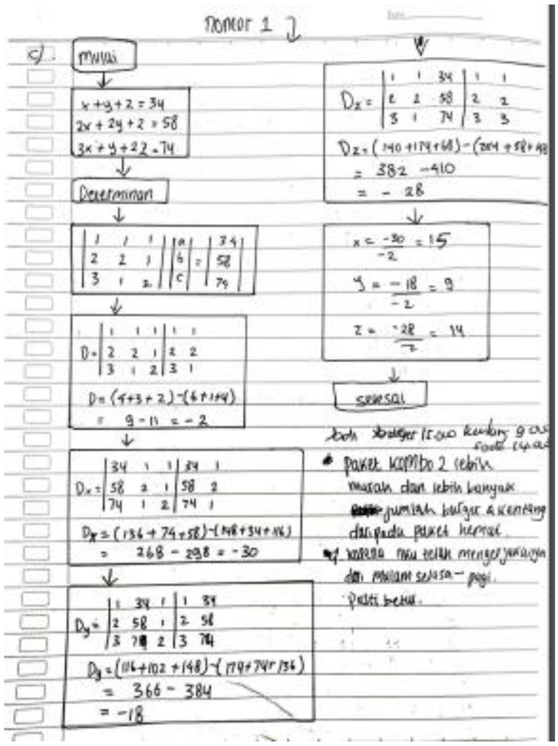
Figure 2. Answer from E35

Algorithmic thinking was demonstrated by the subject in outlining the solution steps. The subject chose to use the determinant method:

"I used a flowchart: first I wrote the three-variable linear equations, then applied the determinant method. Next, I found D, then Dx, Dy, and Dz. I divided Dx, Dy, and Dz by D to obtain x = 15,000; y = 9,000; and z = 14,000."

Thus, student E35 met all the indicators of computational thinking skills: decomposition, pattern recognition, abstraction, and algorithmic thinking.

In contrast, subject E12, although having a high mathematical disposition, made an error in the determinant calculation (Dz), which affected the final result. The subject realized the mistake during the re-substitution process and corrected the incorrect value. The following is the result of subject E12's work.



The student demonstrates decomposition by breaking the problem into three variables (burger, fries, soda) and expressing them in linear equations. Through pattern recognition and abstraction, the student identifies equation structures and represents the situation symbolically as (x,y,z). In algorithmic thinking, the student follows a logical procedure in a flowchart; although an error occurred in calculating Dz, the student recognized and attempted to correct it.

Figure 3. Answer from E12

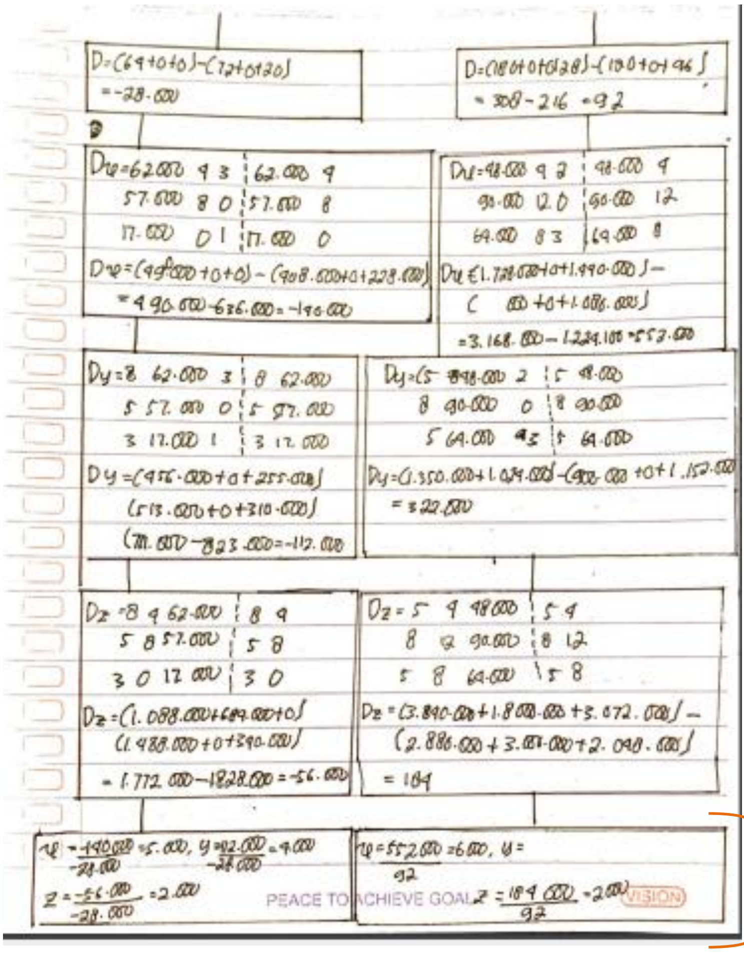
In solving the problem, the subject used the determinant method and created a flowchart to illustrate the steps. However, there was an error in calculating the determinant value of Dz, which initially led to an incorrect final result. Nevertheless, the subject recognized the mistake and attempted to correct it:

"After substituting into equation 1, x + y + z = 34, 15 + 9 + 14 = 38, so something is wrong—it should be 34. For Dz, it should not be 140 but 148, and the result of Dz = –20, so z = (–20) / (–2) = 10, meaning the correct price of the soda is Rp 10,000."

The data from the test results and interviews were consistent, showing that subject E12 was able to reflect on their error and correct it. Thus, although having a high mathematical disposition does not guarantee a completely error-free problem-solving process, students with high disposition, such as E12, can still devise an appropriate problem-solving strategy, identify and correct mistakes, and demonstrate deep conceptual understanding through reflection. Overall, students with a high mathematical disposition can fulfill all indicators of computational thinking skills: decomposition, pattern recognition, abstraction, and algorithmic thinking demonstrated strong but imperfect algorithmic reasoning.

Students' computational thinking skills with a moderate mathematical disposition

The computational thinking skills of students with a moderate mathematical disposition were analyzed based on interview results from two subjects, namely E31 and E29. The third subject (E31), with a mathematical disposition score of 81 (moderate category), obtained a score of 83.33, which falls under the criteria of moderate-level computational thinking skills. Subject E31 was able to solve the problem well, but made some errors.



The student demonstrates decomposition by breaking the problem into three variables and expressing them in linear equations. Through pattern recognition and abstraction, the student identifies equation structures and represents the situation symbolically as (x,y,z). In algorithmic thinking, the student follows a logical procedure in a flowchart; the value of variable y was not provided. The student recognized the mistake and attempted to correct it.

Figure 4. Answer from E31

E31 was able to identify the given information from the problem in detail, namely the stationery packages from store A and store B. The subject also recognized the information being asked, although it was not stated completely. In the answer sheet, the subject only wrote that the question was about finding the price of each stationery item, without explicitly writing the price comparison between store A and store B.

E31 successfully translated the problem information into a mathematical form quite well. They assigned the variables x, y, and z to represent the prices of books, pencils, and erasers, respectively, and then correctly formulated a system of three linear equations for each store. This indicates that the subject had mastered the *abstraction* indicator the ability to transform contextual information into a systematic mathematical representation.

In solving the problem, the subject used the determinant method and wrote the calculation steps in a logical format. They arranged the matrix form, calculated the main determinant, and found the determinants for each variable. However, the calculations were not completed in full there was one variable (y, pencil) that remained unknown by the end of the work, and the conclusion regarding the price of each item in both stores was not stated completely.

"Conclusion: Store A – book Rp 5,000, pencil Rp 4,000, eraser Rp 2,000. Store B – book Rp 6,000, pencil… oh, I haven't written it yet, for the eraser it's Rp 2,000, so for the pencil it's 322,000 ÷ 92 = 3,500."

During the interview, the subject was able to explain their answer quite well, including completing the part that was missing from the written solution. This shows that, conceptually, the subject understood the solving process, but did not fully present it in writing. From the pattern recognition perspective, E31 was able to identify the relationship between the number of stationery items and their total prices in each store, and successfully formulated the correct three-variable linear equation model. This demonstrates the ability to see the structure of data and organize it mathematically. In terms of algorithmic thinking, the subject showed a logical and procedural sequence of steps using the determinant method. They understood the steps needed to solve the system, even though not all results were explicitly stated at the end.

From the triangulation of the test and interview results, consistent and mutually supporting data were obtained. The subject's mistakes were not due to conceptual misunderstanding, but rather incomplete written documentation. Therefore, E31 was able to meet all four indicators of computational thinking decomposition, pattern recognition, abstraction, and algorithmic thinking. The subject could fully identify problem information, create an accurate mathematical model, and solve the problem using logical steps, even without a flowchart visualization. Their verbal explanation demonstrated a thorough understanding of the problem-solving process.

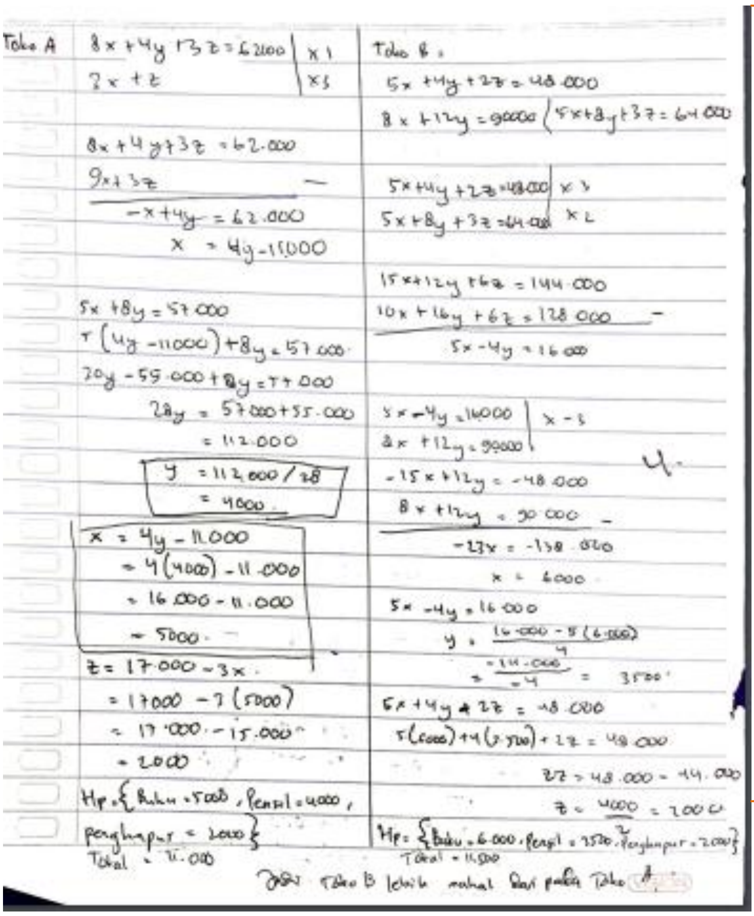
In contrast, subject E29, despite having a moderate mathematical disposition score of 76 and obtaining a score of 70.83, was not able to fully meet all computational thinking indicators. E29 only met the decomposition, pattern recognition, and abstraction indicators, but did not fully demonstrate algorithmic thinking. While the subject was able to outline solution steps and give the correct final conclusion, the elimination and substitution process was not systematic, and no answer verification was conducted. This shows a limitation in organizing and applying a complete problem-solving algorithm.

E29 demonstrated a fair understanding of solving the three-variable system of linear equations using a combined method. The subject was able to identify the given information the prices of various stationery packages from store A and store B and the information being asked, namely the price of each item and the price comparison between the stores. E29 assigned variables x, y, and z to represent the prices of books, pencils, and erasers, and formulated a mathematical model in the form of three linear equations. However, there was an error in writing the initial equations, both in the constants and the equation structure, which the subject acknowledged during the interview:

"Mathematical model for store A: 8x + 4y + 3z = 62,000, 5x + 8y = 37,000, and 3x + z = 17,000. But actually, it should be 57,000 I wrote it wrong."

This shows that although there was an error, the subject had reflective awareness and was able to correct it when prompted. However, in *algorithmic thinking*, the subject's ability was still limited. E29 used the elimination–substitution method, but the sequence of solving steps was not systematic and was not supported by visual aids such as a flowchart. Moreover, the subject did not verify the results by substituting them back into the original equations.

Even so, E29 was able to clearly state the final conclusion, namely the prices of books, pencils, and erasers in each store, and identified that store A was cheaper. Overall, E29 fulfilled three computational thinking indicators decomposition, pattern recognition, and abstractionbut did not meet the algorithmic thinking indicator.



The student demonstrates decomposition by breaking the problem into three variables and formulating them as a system of linear equations. Through pattern recognition and abstraction, the student identifies the equation structures and represents the situation symbolically as (x,y,z). In terms of algorithmic thinking, the student's ability remains limited. The student applies the elimination–substitution method, yet the sequence of steps is less systematic and not supported by visual representation such as a flowchart, resulting in a problem-solving process that is not fully structured logically.

Figure 5. Answer from E29

Participants E31 and E29 showed consistent patterns between their middle mathematical disposition and corresponding CT levels. Regarding flowchart quality and use, E35 produced a complete and accurate flowchart that included all decision points and verification steps, while E29 did not use a flowchart at all, which may have limited their ability to plan algorithmic processes systematically.

Students' computational thinking skills with low mathematical disposition

The mathematical disposition of students in the low category toward computational thinking skills was examined based on interview results from two subjects, namely E32 and E36. The following is a description of the two subjects in relation to the problem they worked on.

Subject E32, with a mathematical disposition score of 68 (low category), obtained a computational thinking score of 62.50, which falls into the low level category. E32 was able to answer the questions, and the following is the result from E32.

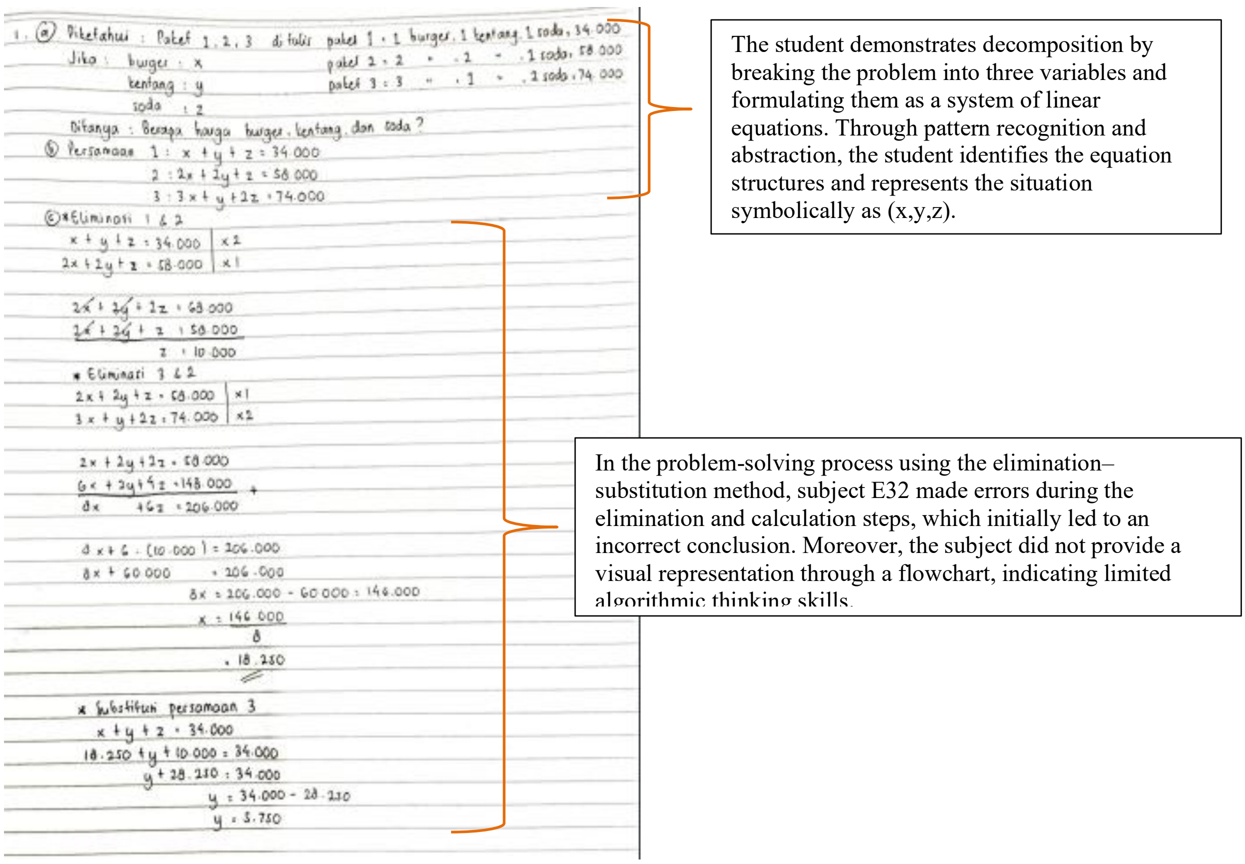


Figure 6. Answer From E32

E32 demonstrated good computational thinking skills in solving the problem, particularly in the indicators of decomposition, pattern recognition, and abstraction, but did not fully meet the indicator of algorithmic thinking. E32 was able to identify the known information from the problem well, namely the contents and prices of each package. The subject also understood what was being asked namely, the individual prices of each item. This indicates achievement in the decomposition indicator, which is the ability to break down a problem into simpler pieces of information.

The subject's ability to construct the relationships between these elements also indicates achievement in the pattern recognition and abstraction indicators, where the subject successfully translated the problem's context into a logical and representative mathematical form.

However, during the solution process using the elimination–substitution method, E32 made errors in both the elimination step and the calculations, which initially led to an incorrect conclusion. The subject also did not use a flowchart for visualization. Nevertheless, E32 realized the mistake and attempted to correct the result:

"So, I changed 6x to –4x, and then 6z to –3z = –90,000, then z became 10,000, giving x = 15,000. Then substituting into equation 1: x + y + z = 34,000, 15,000 + y + 10,000 = 34,000, so y = 9,000."

E32 also verified the result by substituting the variable values back into the original equations, expressing confidence in the final answer. This reflects the benefit of scaffolding, even though the initial procedural errors meant that the algorithmic thinking indicator was not fully met.

This finding was consistent with that of subject E6, who had a mathematical disposition score of 67 (low category) and obtained a computational thinking score of 58.33 (low category). E6 was also only able to meet the indicators of decomposition, pattern recognition, and abstraction, but not algorithmic thinking. E6 could understand the problem information and create a simple mathematical model, but struggled to arrange and execute the problem-solving procedure logically and sequentially. The subject appeared hesitant, confused about which elimination steps to take, and did not verify the final results.

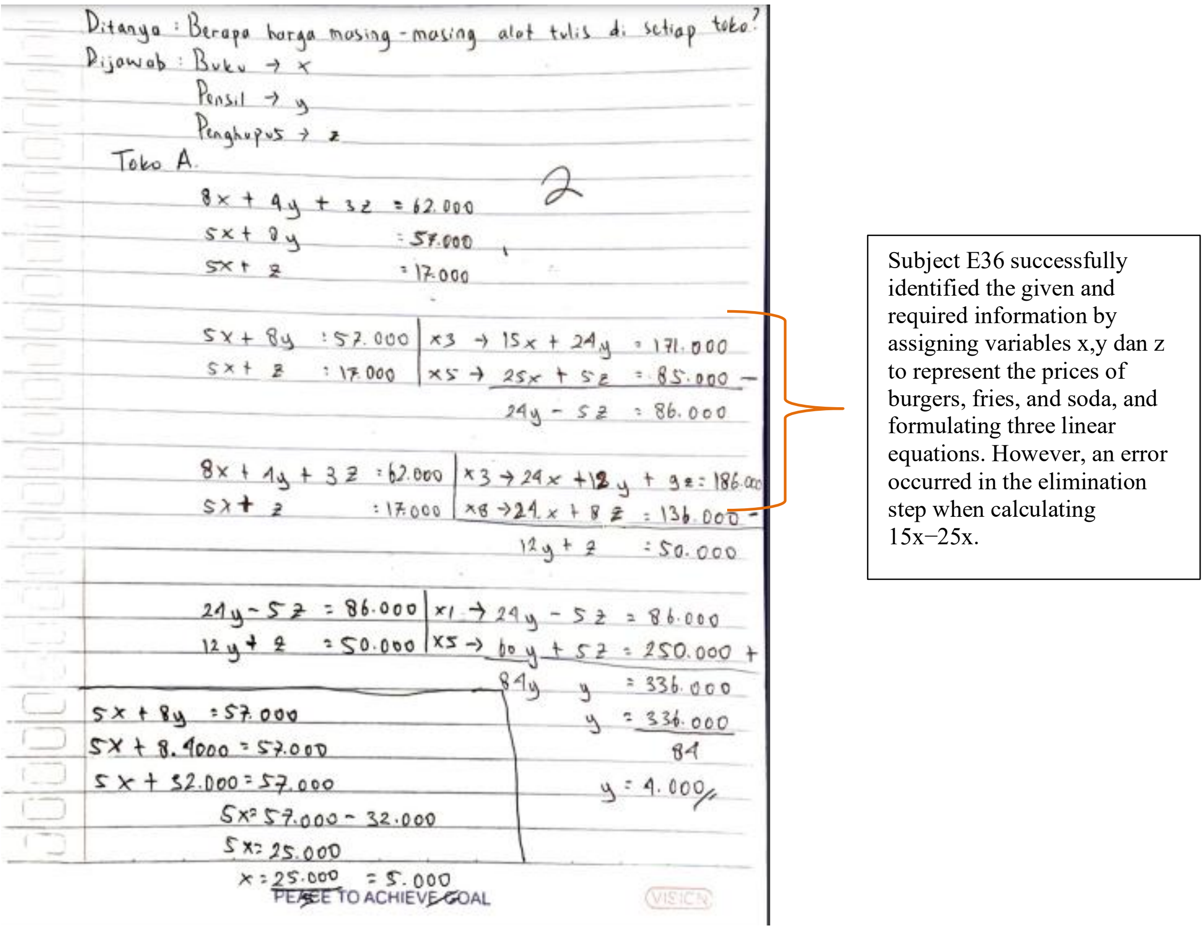


Figure 7. Answer from E36

Subject E36 was able to identify the given information, namely the prices of food packages (burgers, fries, and soda), as well as the required informationthe price of each individual item. E36 correctly assigned variables x, y, and z to represent the prices of burgers, fries, and soda, and set up a mathematical model in the form of three linear equations. However, E36 made an error in the elimination step, specifically in calculating 15x – 25x:

“I changed 25x to 15x, so 15x – 15x = 0, and equation 3 should be 3x + z = 17,000.”

After scaffolding, the subject was able to revise the solution and check it against the given equations. E36 concluded that for store A, the prices were: book = Rp 5,000, pencil = Rp 4,000, and eraser = Rp 2,000. However, E36 did not complete the solution for the entire problem, and was only able to solve for store A.

"I haven't gotten that far yet. I don't know which one I should eliminate first."

This indicates that while E36 was able to manage most of the problem-solving steps, they still need to improve accuracy in managing calculations and working with larger numbers. In terms of algorithmic thinking, E36 was unable to produce logical and systematic steps. Overall, E36 met three computational thinking indicators decomposition, pattern recognition, and abstraction but did not meet the algorithmic thinking indicator.

At the same time, the results revealed no participants with high CT disposition who exhibited low CT performance. This consistency indicates that while scaffolding provides significant benefits for learners with low or medium dispositions, students with high dispositions may have already achieved their optimal performance level. Consequently, this suggests a potential ceiling effect or selection bias within the sample, where high-achieving participants dominate the upper range of computational thinking outcomes.

The following are the results of the analysis of computational thinking skills based on students' levels of mathematical disposition. The symbol "√" indicates that the indicator was achieved.

Table 4. Computational thinking skills in terms of students' mathematical disposition

Student Code	Mathematical Disposition		Computational Thinking		Decomposition	Pattern Recognition	Abstraction	Algorithmic Thinking
E35	High	112	High	100	√	√	√	√
E12	High	105	High	91.67	√	√	√	√
E31	Medium	81	Medium	83.33	√	√	√	√
E29	Medium	76	Medium	70.83	√	√	√	–
E32	Low	68	Medium	62.50	√	√	√	–
E36	Low	67	Low	58.33	√	√	√	–

Discussion

The grouping of students' mathematical dispositions had previously been categorized into three levels: high, medium, and low. From each category, two subjects were selected to analyze their computational thinking abilities. Mathematical disposition plays an essential role in developing students' computational thinking skills (Pérez, 2018).

Students with a high mathematical disposition, such as subjects E35 and E12, consistently demonstrated high performance across all computational thinking indicators decomposition, pattern recognition, abstraction, and algorithmic thinking. Both subjects were able to identify problem information in detail, construct a mathematical model in the form of a Three-Variable System of Linear Equations, and solve it using the determinant method illustrated through a flowchart. The flowchart served to display the algorithmic thinking indicator (Azmi & Ummah, 2021), showing logical and systematic problem-solving steps. This indicates that a high mathematical disposition does not completely eliminate the possibility of errors. However, students with such dispositions tend to possess strong reflective and metacognitive abilities, enabling them to arrive at the correct solution through systematic and critical thinking. High mathematical disposition students also tend to take greater responsibility for their own learning and consistently cultivate good mathematical habits. The observation that high-disposition students showed greater initiative and persistence may reflect components of Self-

Determination Theory, particularly the needs for autonomy and competence (Ryan & Deci, 2000). These students appeared more confident in exploring alternative strategies without external prompts, demonstrating intrinsic motivation consistent with Zan et al. (2006), affective model of mathematical engagement, which emphasizes the role of emotional and motivational factors in shaping mathematical behavior.

Students with a medium mathematical disposition, such as subjects E31 and E29, showed good results in computational thinking. The outcomes varied: one subject fulfilled all four indicators decomposition, pattern recognition, abstraction, and algorithmic thinking while the other only fulfilled up to the abstraction indicator. The limitation was caused by minor errors during problem-solving. In terms of algorithmic thinking, these students tended to be less systematic in their problem-solving steps, especially in creating flowcharts or performing variable elimination. However, with scaffolding, they were able to correct errors and reach the correct solution. Scaffolding plays an important role in helping students optimize their thinking abilities in solving mathematical problems (Fanchamps et al., 2021; Kamak & Mago, 2023; Romero & Ouellet, 2016). It can support and enhance students' computational thinking by providing guiding questions, hints, reminders, directions, or prompts that encourage maximum engagement with computational thinking. This was evident from their progress, moving from only recognizing patterns to achieving abstraction and algorithmic thinking in mathematical problem solving (Supiarmo et al., 2021).

Students with a low mathematical disposition, such as E32 and E36, were able to fulfill the decomposition, pattern recognition, and abstraction indicators but struggled with algorithmic thinking. While they could understand problem information and develop a mathematical model, they often made errors in calculations or equation-solving and were unable to create flowcharts to represent systematic and logical solution steps. After receiving scaffolding, E32 was able to correct mistakes, solve problems accurately, and draw appropriate conclusions. However, E36 could not correct errors, complete the problem correctly, or provide a suitable conclusion. Incomplete solution steps included failing to break down the given and required information, making computational mistakes, and not drawing a conclusion from the solution. These issues prevented them from reaching the algorithmic thinking stage of computational thinking (Supiarmo et al., 2021). Research by Sofiatun also shows that students with low dispositions often fail to meet all computational thinking indicators, with low affective attitudes generally fulfilling only the decomposition indicator (Azizia et al., 2023).

However, this study reinforces that proper scaffolding during the learning process can help low-disposition students reach higher-order thinking stages, such as abstraction. This aligns with observations showing that students who previously could only organize basic information were able through guiding questions, examples, and visual aids like flowcharts to identify patterns and develop systematic solution steps. Therefore, a scaffolding-assisted learning strategy proves effective in bridging the gap between mathematical disposition and computational thinking ability. Students who initially struggled to understand problem structures can be gradually guided to develop more abstract and structured problem-solving strategies, particularly for complex topics such as the three-variable system of linear equations.

Moreover, the findings indicate that enhancing the CT skills of students with medium and low mathematical dispositions requires structured scaffolding, such as probing questions, hints, and partially completed flowcharts that guide them toward systematic reasoning (Reiser, 2018). During the interview sessions, scaffolding was provided consistently across participants through guided questioning, explicit cues, and motivational prompts, which helped them organize their problem-solving steps and correct conceptual errors. Nevertheless, it should also be noted that for some low-disposition students, the use of flowcharts might introduce additional cognitive load, as they struggled to translate abstract relationships into visual forms (Weintrop et al., 2016).

These findings highlight that a scaffolding-assisted learning strategy is effective in bridging the gap between mathematical disposition and computational thinking ability, particularly in the context of Indonesian classrooms, where teacher-centered instruction often limits students' autonomy and initiative (Doloma et al., 2020). Providing structured guidance within such environments can therefore serve as a compensatory mechanism that supports students in developing both conceptual understanding and problem-solving independence.

Conclusion

This study demonstrates that mathematical disposition functions not as a fixed trait but as a dynamic enabler of computational thinking, shaping how students engage in problem solving and reasoning. Students with higher mathematical disposition levels tend to organize their thoughts more systematically and engage more deeply with computational thinking indicators decomposition, pattern recognition, abstraction, and algorithmic thinking, particularly when supported by visual scaffolds such as flowcharts. Conversely, students with medium and low dispositions benefit significantly from structured scaffolding that helps them internalize these indicators in a gradual and reflective manner.

In practice, enhancing students' computational thinking can be achieved through three targeted strategies: (1) Partial flowcharts, which strengthen algorithmic thinking by helping learners visualize logical sequences step by step; (2) Think-aloud protocols, which support decomposition and abstraction as students articulate and reorganize their reasoning; and (3) Growth mindset interventions, which enhance pattern recognition and persistence by fostering confidence and positive learning attitudes. Together, these strategies show that scaffolding and disposition-building activities can bridge affective and cognitive aspects of computational learning.

Future research should include experimental studies testing flowchart-based scaffolding interventions across different levels of mathematical disposition to establish causal relationships between disposition and computational thinking performance. Additionally, longitudinal and cross-cultural studies are encouraged to examine how cultural norms, instructional styles, and motivational factors shape the long-term development of computational thinking and mathematical disposition.

Acknowledgment

The authors would like to thank the Institute for Research and Community Service of Semarang State University (LPPM UNNES) for the support and funding in the preparation and publication of this article. This article was funded through DANA DPA LPPM UNNES YEAR 2025 with Number: 374.14.3/UN37/PPK.11/2025. This support is very meaningful in encouraging the development of research and scientific publications in the academic environment.

Conflicts of Interest

The authors declare no conflict of interest regarding the publication of this manuscript. In addition, the authors have completed the ethical issues, including plagiarism, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies.

Funding Statement

Institute for Research and Community Service of Semarang State University (LPPM UNNES) for the support and funding in the preparation and publication of this article. This article was funded through DANA DPA LPPM UNNES YEAR 2025 with Number: 374.14.3/UN37/PPK.11/2025.

Author Contributions

Ananda Jullailatul Azizia: Conceptualization, methodology, data curation, writing-original draft, and visualization; **Masrukan:** Review, providing input, supervision, project administration, and final approval of the manuscript; **Bambang Eko Susilo:** Formal analysis, writing – review & editing, and validation; **Ahmad Arifuddin:** Development of the mathematical disposition questionnaire, review, and validation.

References

Angeli, C. (2022). The effects of scaffolded programming scripts on pre-service teachers' computational thinking: Developing algorithmic thinking through programming robots. *International Journal of Child-Computer Interaction*, *31*. https://doi.org/10.1016/j.ijcci.2021.100329

Azizia, A. J., Kusmaryono, I., Maharani, H. R., & Arifuddin, A. (2023). Students' computational thinking process in solving PISA problems of change and relationship content reviewed from students' self efficacy. *EduMa: Mathematics Education Learning and Teaching*, *12*(1), 112–125. https://doi.org/10.24235/eduma.v12i1.13132

Azizia, A. J., Masrukan, & Susilo, B. E. (2024). Systematic literature review: Trends computational thinking and mathematical disposition in mathematics learning. *Kontinu: Jurnal Penelitian Didaktik Matematika*, *8*(2), 152–169. https://doi.org/10.53115/19975996_2024_02_083_092

Azmi, R. D., & Ummah, S. K. (2021). Implementasi project based learning untuk mengeksplorasi kemampuan computational thinking mahasiswa [Implementation of project-based learning to explore students' computational thinking skills. *Jurnal Ilmiah Pendidikan Matematika Al Qalasadi*, *5*(1), 52–61. https://doi.org/10.32505/qalasadi.v5i1.2761

Begum, S., Flowers, N., Tan, K., Carpenter, D. M. H., & Moser, K. (2021). Promoting literacy and numeracy among middle school students: Exploring the mediating role of self-efficacy and gender differences. *International Journal of Educational Research*, *106*, 101722. https://doi.org/10.1016/j.ijer.2020.101722

Calao, L. A., Moreno-León, J., Correa, H. E., & Robles, G. (2015). Developing mathematical thinking with scratch an experiment with 6th grade students. In K. J, K. T, R. Christoph, C. G, & L. É (Eds.), *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics* (Vol. 9307, pp. 17–27). Springer Verlag. https://doi.org/10.1007/978-3-319-24258-3_2

Chinofunga, M. D., Chigeza, P., & Taylor, S. (2025). How can procedural flowcharts support the development of mathematics problem-solving skills? *Mathematics Education Research Journal*, *37*(ue 1)). https://doi.org/10.1007/s13394-024-00483-3

Clark, J. M., & Paivio, A. (1991). Dual coding theory and education. *Educational Psychology Review*, *3*(3), 149–210. https://doi.org/10.1007/BF01320076

Cromley, J. G., & Chen, R. (2024). Instructional support for visual displays: An updated literature review. *Technology, Knowledge and Learning*, *29*(3), 1191–1205. https://doi.org/10.1007/s10758-023-09699-x

Doleck, T., Bazelais, P., Lemay, D. J., Saxena, A., & Basnet, R. B. (2017). Algorithmic thinking, cooperativity, creativity, critical thinking, and problem solving: exploring the relationship between computational thinking skills and academic performance. *Journal of Computers in Education*, *4*(4), 355–369. https://doi.org/10.1007/s40692-017-0090-9

Doloma, D., Kambas, A., Aggeloussis, N., & Michalopoulou, M. (2020). A longitudinal study for the relationship between motor coordination and body mass index in primary school children. *International Journal of Instruction*, *13*(3), 511–524. https://doi.org/10.29333/iji.2020.13335a

Elicer, R., Tamborg, A. L., Bråting, K., & Kilhamn, C. (2023). Comparing the integration of programming and computational thinking into Danish and Swedish elementary mathematics curriculum resources. *Iron and Steel Technology*, *11*(3), 77–102. https://doi.org/10.31129/LUMAT.11.3.1940

Fanchamps, N. L. J. A., Slangen, L., Hennissen, P., & Specht, M. (2021). The influence of SRA programming on algorithmic thinking and self-efficacy using Lego robotics in two types of instruction. *International Journal of Technology and Design Education*, *31*(2), 203–222. https://doi.org/10.1007/s10798-019-09559-9

Firmasari, S., Nopriana, T., & Pujiana, F. (2025). Computational thinking Skills from the perspective of students' self-confidence in mathematics learning. *Indonesian Research Journal in Education| IRJE*, *9*(01), 509–525. https://doi.org/10.22437/irje.v9i01.37228

Fleur, D. S., Bredeweg, B., & Bos, W. (2021). Metacognition: ideas and insights from neuro- and educational sciences. *Npj Science of Learning*, *6*(1), 1–13. https://doi.org/10.1038/s41539-021-00089-5

Hariyani, L., Yurniwati, Y., & Utami, A. D. (2024). The effect of discovery learning in mathematics learning on computational thinking in terms of self-regulated learning (SRL) in student. *Jurnal Elementaria Edukasia*, *7*(2), 2801–2814. https://doi.org/10.31949/jee.v7i2.9551

Isharyadi, R., & Juandi, D. (2023). A systematics literature review of computational thinking in mathematics education: Benefits and challenges. *Formatif: Jurnal Ilmiah Pendidikan MIPA*, *13*(1), 69–80. https://doi.org/10.30998/formatif.v13i1.15922

Jong, M. S. Y., Geng, J., Chai, C. S., & Lin, P. Y. (2020). Development and predictive validity of the computational thinking disposition questionnaire. *Sustainability (Switzerland*, *12*(11). https://doi.org/10.3390/su12114459

Kamak, L. P., & Mago, V. (2023). Assessing the impact of using python to teach computational thinking for remote schools in a blended learning environment. In Z. P, I. A, & I. A (Eds.), *LNCS* (Vol. 14041, pp. 482–500). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1007/978-3-031-34550-0_35

Kayhan, O., Korkmaz, Ö., & Çakır, R. (2024). How do computational thinking and logical and math thinking skills predict programming self-efficacy? *Computers in the Schools*, *41*(1), 51–73. https://doi.org/10.1080/07380569.2023.2220696

Kusmaryono, I., Suyitno, H., Dwijanto, D., & Dwidayati, N. (2019). The effect of mathematical disposition on mathematical power formation: review of dispositional mental functions. *International Journal of Instruction*, *12*(1), 343–356. https://doi.org/https://eric.ed.gov/?id=EJ1201186

Lee, S. W. Y., Tu, H. Y., Chen, G. L., & Lin, H. M. (2023). Exploring the multifaceted roles of mathematics learning in predicting students' computational thinking competency. *International Journal of STEM Education*, *10*(1). https://doi.org/10.1186/s40594-023-00455-2

Maharani, S., Nusantara, T., As'ari, A. R., & Qohar, A. (2019). How the students computational thinking ability on algebraic? *International Journal of Scientific and Technology Research*, *8*(9), 419–423.

Mertens, A. J., & Colunga, E. (2025). Assessing cognitive components of computational thinking. *Frontiers in Psychology*, *16*. https://doi.org/10.3389/fpsyg.2025.1434453

Muhammad, I., Rusyid, H. K., Maharani, S., & Angraini, L. M. (2023). Computational thinking research in mathematics learning in the last decade: A bibliometric review. *International Journal of Education in Mathematics, Science and Technology*, *12*(1), 178–202. https://doi.org/10.46328/ijemst.3086

NCTM. (2000). *Principles and standards for school mathematics*. The National Council of Teachers of Mathematics, Inc.

Nordby, S. K., Bjerke, A. H., & Mifsud, L. (2022). Computational thinking in the primary mathematics classroom: A systematic review. *Digital Experiences in Mathematics Education*, *8*(1), 27–49. https://doi.org/10.1007/s40751-022-00102-5

Pérez, A. (2018). A framework for computational thinking dispositions in mathematics education. *Journal for Research in Mathematics Education*, *49*(4), 424–461. https://doi.org/10.5951/jresematheduc.49.4.0424

Psycharis, S., & Kotzampasaki, E. (2019). The impact of a STEM inquiry game learning scenario on computational thinking and computer self-confidence. *Eurasia Journal of Mathematics, Science and Technology Education*, *15*(4), 1689. https://doi.org/10.29333/ejmste/103071

Rahman, M. M., Sharker, M. H., & Paudel, R. (2020, 2020). *An effective approach to teach an introductory computer science course with computational thinking and flow-chart based visual programming* Proceedings - Frontiers in Education Conference, FIE, http://dx.doi.org/10.1109/FIE44824.2020.9273930

Ramaila, S., & Shilenge, H. (2023). Integration of computational thinking activities in Grade 10 mathematics learning. *International Journal of Research in Business and Social Science*, *12*(2), 458–471. https://doi.org/10.20525/ijrbs.v12i2.2372

Reiser, B. J. (2018). Scaffolding complex learning: The mechanisms of structuring and problematizing student work. *Scaffolding: A Special Issue of the Journal of the Learning Sciences*, *13*(3), 273–304. https://doi.org/10.4324/9780203764411-2

Romero, M., & Ouellet, H. (2016). Scaffolding digital game design activities grouping older adults, younger adults and teens. In Z. J & S. G (Eds.), *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics* (Vol. 9754, pp. 74–81). Springer Verlag. https://doi.org/10.1007/978-3-319-39943-0_8

Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary Educational Psychology*, *25*(1), 54–67.

Schraw, G., & Richmond, A. S. (2022). Using visual displays to improve classroom thinking. *Educational Research: Theory and Practice*, *33*(2), 80–102. https://doi.org/https://eric.ed.gov/?id=EJ1352339

Sezer, H. B., & Namukasa, I. K. (2023). School and community practices of computational thinking in mathematics education through diverse perspectives. *Journal of Research in Science,* *Mathematics and Technology Education*, *6*(SI), 137–160. https://doi.org/10.31756/jrsmte.617si

Silverman, D. (2021). Doing qualitative research.

Solitro, U., Pasini, M., Gradi, D., & Brondino, M. (2017). A preliminary investigation on computational abilities in secondary school. In H. A & D. V (Eds.), *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics* (Vol. 10696, pp. 169–179). Springer Verlag. https://doi.org/10.1007/978-3-319-71483-7_14

Suarsana, I. M., Herman, T., Nurlaelah, E., Irianto, & Pacis, E. R. (2024). Computational thinking in mathematics education across five nations. *Indonesian Journal of Educational Research and Review*, *7*(1), 26–35. https://doi.org/10.23887/ijerr.v7i1.68202

Supiarmo, M. G., Mardhiyatirrahmah, L., & Turmudi, T. (2021). Pemberian scaffolding untuk memperbaiki proses berpikir komputasional siswa dalam memecahkan masalah matematika [Providing scaffolding to improve students' computational thinking processes in solving mathematical problems. *Jurnal Cendekia : Jurnal Pendidikan Matematika*, *5*(1), 368–382. https://doi.org/10.31004/cendekia.v5i1.516

Supiarmo, M. G., Sholikin, N. W., Harmonika, S., & Gaffar, A. (2022). Implementasi pembelajaran matematika realistik untuk meningkatkan kemampuan berpikir komputasional siswa [Implementation of realistic mathematics learning to improve students' computational thinking skills. *Numeracy*, *9*(1), 1–13. https://doi.org/10.46244/numeracy.v9i1.1750

Tang, Y., & Ma, X. (2023, 2023). *Can computational thinking contribute to EFL learning and teaching?* Proceedings - 2023 International Conference on Artificial Intelligence and Education, ICAIE 2023, http://dx.doi.org/10.1109/ICAIE56796.2023.00016

Threekunprapa, A., & Yasri, P. (2020). Unplugged coding using flowblocks for promoting computational thinking and programming among secondary school students. *International Journal of Instruction*, *13*(3), 207–222. https://doi.org/10.29333/iji.2020.13314a

Wang, L. (2023). The impact of student-centered learning on academic motivation and achievement: A comparative research between traditional instruction and student-centered approach. *Journal of Education, Humanities and Social Sciences*, *22*, 346–353. https://doi.org/10.54097/ehss.v22i.12463

Wardani, S. S., Susanti, R. D., & Taufik, M. (2022). Implementasi pendekatan computational thinking melalui game jungle adventure terhadap kemampuan problem solving [Implementation of computational thinking approach through jungle adventure games on problem solving skills. *SJME (Supremum Journal of Mathematics Education*, *6*(1), 1–13. https://doi.org/10.35706/sjme.v6i1.5430

Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016). Defining computational thinking for mathematics and science classrooms. *Journal of Science Education and Technology*, *25*, 127–147. https://doi.org/10.1007/s10956-015-9581-5

Wing, J. (2017). Computational thinking's influence on research and education for all. *Italian Journal of Educational Technology*, *25*(2), 7–14. https://doi.org/https://www.learntechlib.org/p/183466/

Zan, R., Brown, L., Evans, J., & Hannula, M. S. (2006). Affect in mathematics education: An introduction. *Educational Studies in Mathematics*, *63*(2), 113–121. https://doi.org/https://www.jstor.org/stable/25472116

Zhang, J. H., Meng, B., Zou, L. C., Zhu, Y., & Hwang, G. J. (2023). Progressive flowchart development scaffolding to improve university students' computational thinking and programming self-efficacy. *Interactive Learning Environments*, *31*(6), 3792–3809. https://doi.org/10.1080/10494820.2021.1943687