

How Do Computational Thinking Skills Support Secondary Students in Solving Complex Mathematical Pattern Problems?

Maulida Aulia^{1*}, Sri Suryanti¹, Li Long²

¹Mathematics Education Department, Universitas Negeri Surabaya, Indonesia

²Education Department, Tongren University, China

maulida.23163@mhs.unesa.ac.id

ABSTRACT

Article History:

Received : 07-05-2026

Revised : 30-06-2026

Accepted : 03-07-2026

Online : 20-10-2026

Keywords:

Computational Thinking Skill;

Mathematics Problem

Solving;

Complex Number

Pattern;

Abstraction;

Algorithmic Thinking.



Abstract: Solving complex number pattern problems not only involves detecting the regularity of the numbers but also involves generalizing the pattern, filtering relevant information, and formulating problem solutions. However, many secondary students have continued to rely on procedural strategies and have failed to employ higher-order cognitive processes in problem-solving tasks. This research investigates how computational thinking (CT) skills facilitate lower secondary students' ability to solve complex number-pattern problems. In addition, the research aims to identify the most prominent CT indicators among the other indicators. The research employed an exploratory case study approach using both quantitative and qualitative methods. Twenty-seven eighth-grade students from a private institution in Indonesia participated in the research. Data were gathered through an open-ended problem-solving test on complex number patterns and through semi-structured interviews with students, using stimulated recall techniques. The quantitative data analysis included descriptive analysis in identifying the levels of CT indicators achieved by the students. On the other hand, the qualitative data analysis involved thematic analysis of the answers on the answer sheets and the interviewees' statements, in accordance with the four CT indicators: decomposition, pattern recognition, abstraction, and algorithmic thinking. The findings show that most students were only able to attain the beginning-to-middle stages of CT. Specifically, pattern recognition (30.80%) and decomposition (23.10%) received the most attention among the students. In contrast, very few students achieved the CT stage of abstraction and algorithmic thinking (7.70%). These results imply that CT is very important for students, enabling them to analyze information and discover regularities. Nonetheless, the problem faced by the students is that of finding solutions for these regularities and making algorithms. As such, there is a need to incorporate computational thinking in mathematics, particularly when teaching students about number sequences. Implications would be providing students with more difficult problems to solve.



<https://doi.org/10.31764/jtam.v10i4.39590>



This is an open access article under the **CC-BY-SA** license

A. INTRODUCTION

The 21st-century transformation of education, characterized by the integration of information technology and digitalization, requires students to possess relevant thinking skills to adapt and compete globally. One of the key skills required is computational thinking (CT) (Cahdriyana et al., 2020; Lee et al., 2020; Peracaula-Bosch et al., 2024). The term CT was first introduced by Seymour Papert in 1980 and popularized by Jeannette Wing in 2006 (Lodi & Martini, 2021). Computational Thinking (CT) is considered to be one of the key abilities in solving 21st century problems using a structured and multidisciplinary approach to problem-

solving (Amri et al., 2019; Yadav et al., 2017). According to Wing (2006), computational thinking (CT) is a thought process involving problem formulation and solution development using computing concepts. This process includes the ability to break down complex problems into simpler parts, identify patterns and relationships, and develop algorithms as problem-solving strategies (Helsa et al., 2023). Therefore, CT is one of the key competencies that needs to be developed in 21st-century learning.

Within mathematics education, CT can be said to provide a cognitive basis for problem solving by assisting the learners to break down the problems and come up with logical solutions grounded on their deeper understanding of the problems, and not simply going through the procedural way (Subramaniam et al., 2022; Voon et al., 2022). In line with this role, CT also supports effective problem-solving in mathematics education. Problem-solving is understood as a systematic thinking process that involves understanding the problem, planning strategies, implementing solutions, and evaluating results in a logical and structured manner (Rott et al., 2021). The development of CT abilities is increasingly important at the lower secondary level due to the development of the ability to think abstractly, which means that the ability to critically solve problems is essential (Rabillas et al., 2024). The learners at this level are presented with math problems requiring analytical thinking. Thus, strengthening CT in lower secondary school students is a crucial step toward supporting their success in solving complex mathematical problems. To develop students' computational thinking (CT) skills in mathematics learning, four interrelated CT processes, including decomposition, pattern recognition, abstraction, and algorithmic thinking, are necessary for building effective problem-solving strategies (Maulina & Khusna, 2024).

One area of mathematics closely related to CT is number patterns, which are understood as regularities or specific arrangements and are often integrated into everyday problem-solving (Mulligan & Mitchelmore, 2009). At the lower secondary school level, number pattern problems are no longer limited to determining the first few terms of a simple sequence but also include finding specific terms that require generalization and symbolic representation. As the subject evolves, number patterns are presented not only in simple forms but also in more complex forms, such as quadratic or recursive patterns, which require the coordination of numerical, tabular, and symbolic representations (Purwasih et al., 2024). These conditions require students to recognize regularities, identify relationships among patterns, and systematically derive general rules. This process directly involves the key components of computational thinking: decomposition, pattern recognition, abstraction, and algorithmic thinking (Udvaros et al., 2023). Furthermore, the role of computational thinking becomes increasingly significant in complex patterns because students need to identify non-constant changes and deeply understand the relationships between patterns (Wilkie & Ayalon, 2018).

The incorporation of computational thinking (CT) in different areas of learning helps in building up the cognitive skills of students, especially systematic problem solving, algorithmic thinking, and developing data-based solutions (Palop et al., 2025; Peng et al., 2025). In line with this, CT is directly linked with reasoning and problem solving skills of students. This result is consistent with previous literature Susanti & Taufik (2021) which shows that incorporation of CT gives a conceptual model of thinking which allows students to pay more attention to problem-solving activities. Likewise, Asbar et al. (2026) show that CT processes such as

decomposition and abstraction strengthen problem-solving skills through mathematics. Also, pattern recognition is a key step in utilizing problem-solving strategies in similar situations. Therefore, having a good understanding of basic CT concepts is very important to integrate CT in learning to develop systematic problem-solving skills in secondary level students.

Chan et al. (2021) found a relationship between CT and students' ability to solve number pattern problems as well as mathematical problems requiring higher-order thinking strategies. The above findings are consistent with the study done by Ye et al. (2023) who found that integrating CT in teaching mathematics improves students' problem-solving skills, mathematical reasoning, and high-order thinking skills. Besides, according to Wu et al. (2024), CT helps students adopt a better strategy for problem solving. Other studies have confirmed that pattern recognition in CT is fundamental in helping students recognize patterns while solving mathematical problems (Taufik et al., 2024). Overall, all the above findings show that CT contributes significantly to students' mathematical thinking process.

However, in practice, many students still struggle to identify patterns and make generalizations, and they tend to rely on formulas (Maula et al., 2024). This is consistent with a study by Iskandar et al. (2025) showing that lower secondary school students in Indonesia have difficulty identifying regularities in number patterns, accurately generalizing patterns, and explaining the processes they use to solve mathematical problems. Similar findings were reported by Apriandi et al. (2023), who showed that students still face obstacles in pattern recognition, abstraction, and generalization when solving number-pattern problems. Furthermore, the results of a study by Firdaus et al. (2026) indicate that the indicators of abstraction (45%) and algorithmic reasoning (35%) showed lower achievement levels than other computational thinking (CT) indicators. These difficulties in identifying patterns, making generalizations, and explaining problem-solving processes suggest that students' computational thinking skills have not yet developed to an optimal level.

The novelty of this study lies in its empirical analysis of CT's role in solving complex number-pattern problems among secondary students. In contrast to previous studies, which have focused mainly on CT skills as they apply to coding tasks or the integration of technology, this current study examines the formation of CT skills in the process of working on math tasks, especially number patterns. This study provides information about the way that the decomposition, pattern recognition, abstraction, and algorithm skills are used by students while tackling difficult number-pattern questions. In this regard, number patterns are viewed as an effective medium for combining mathematics and CT. Therefore, this study aims to bridge the empirical gap by thoroughly examining the role of CT in helping students solve complex number-pattern problems. By analyzing how students break down problems, recognize patterns, perform abstraction, and systematically formulate solution steps, this study is expected to provide a deeper understanding of the cognitive processes underlying mathematical problem-solving.

Furthermore, the results of this study are expected to contribute to the development of learning strategies to strengthen CT in mathematics education. Based on this, the research questions formulated in this study are: (1) How do CT skills help students solve complex number pattern problems?; and (2) Which CT skill indicator contributes most to solving complex number pattern problems?

B. METHODS

1. Research Design

The present research uses a mixed methods design under the exploratory case study design to understand how CT helps the students solve complex number pattern problems. Mixed methods design ensures that the data can be integrated between quantitative and qualitative aspects, which leads to a more comprehensive understanding of any complex educational phenomenon. For instance, quantitative data is used to assess the performance of students in solving complex number pattern problems, whereas the qualitative data is used to understand the CT process of the students while solving problem. Klik atau ketuk di sini untuk memasukkan teks.s.

2. Participant

The participants in this study consisted of 27 eighth-grade students at a private school in Indonesia. Participants for this study were identified through purposive sampling based on criteria including having worked with number patterns, willingness to participate in the research exercises, and ability to solve the assigned problems. Purposive sampling was used because it allows the selection of participants who are directly relevant to the study's goals, thus providing more detailed insight into the phenomena under investigation (Taherdoost, 2016). Eighth-grade students were selected because they already have a basic understanding of number patterns and are at a stage of cognitive development that supports observation of the CT process. Before the study was conducted, all participants were informed of the study's objectives and procedures, and they expressed their willingness to participate in accordance with the ethical principles of educational research (Golding & Ince, 2024). Additionally, to provide a more comprehensive overview of students' characteristics with respect to mathematical ability, the data are presented in Table 1.

Table 1. Student Characteristics in Mathematical Ability

Characteristics		Number of students	Percentage
Gender	Male	17	62,96%
	Female	10	37,04%
Mathematical Ability	High	7	25,93%
	Currently	15	55,56%
	Low	5	18,52%

3. Data Collection

Data in this study were collected using several methods to gain a comprehensive understanding of students' cognitive processes in solving complex number-pattern problems. First, quantitative data were obtained through a structured problem-solving test designed to assess students' ability to recognize patterns, make generalizations, and develop problem-solving strategies aligned with predetermined CT indicators. Second, qualitative data were collected through the analysis of students' answer sheets and semi-structured interviews with selected students. The interviews were conducted after students completed the problem-solving tasks, using the stimulated recall technique, in which they were asked to review the written answers they had provided and explain the steps they took to solve the problems, as

well as the reasoning behind each decision made during the problem-solving process. This technique allows researchers to explore students' thought processes in greater depth and identify the emergence of CT indicators (decomposition, pattern recognition, abstraction, and algorithmic thinking) during problem-solving (Zhai et al., 2024). Interview data also serves to confirm the results of the analysis of written responses while deepening the understanding of the contribution of each CT indicator in solving complex number pattern problems (Adeoye-olatunde & Olenik, 2021)

4. Research Stages

This study was conducted in four stages. The first stage was to select the students who would participate in the study. The second stage was to give the students problem-solving questions involving complex number patterns. The third stage involved analyzing the students' written answers and conducting semi-structured interviews to assess their computational thinking abilities. The fourth stage was to analyze the data using computational thinking indicators to identify the most dominant ones. The complete research flowchart is presented in Figure 1.

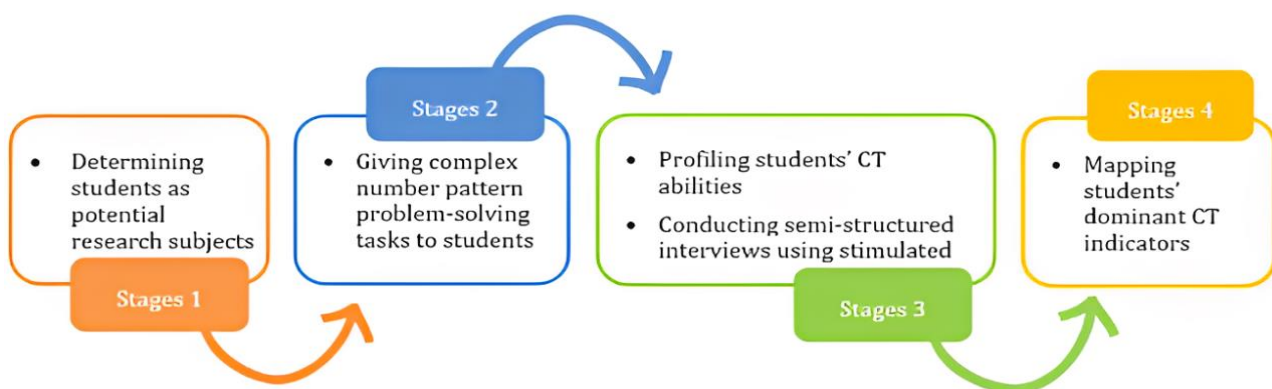


Figure 1. Research Stages

5. CT Measurement Indicators

To analyze students' computational thinking (CT) skills in solving complex number-pattern problems, this study employed four CT indicators: decomposition, pattern recognition, abstraction, and algorithmic thinking. These indicators were used as the basis for analyzing students' written responses and interview data. The operational definitions of each indicator are presented in Table 2.

Table 2. Indicators of CT Ability

Indicators	Description
Decomposition	Breaking down complex problems or processes into smaller, more manageable parts (subproblems).
Pattern Recognition	Identifying similarities, patterns, or recurring elements in two or more pieces of information.
Abstraction	Identifying important and relevant information while disregarding unnecessary details to identify and generalize patterns.
Algorithmic Thinking	Developing systematic steps or instructions to describe the process of generating solutions.

Adapted from (Astuti et al., 2025)

6. Instrument

Two different data gathering tools were used for this study, namely the problem solving test and the interviewing protocol. For the principal tool, only one open-ended test was used to capture the cognitive-textual (CT) processes of the students when they tackled number pattern problems. Simultaneously, the interviewing protocol was used not only to get insights about the problem solving process of the students but also to determine the CT processes that significantly affected problem solving based on the CT assessment principle wherein thought processes are revealed and not the solution alone.

"At Tirta Bangsa Middle School, there are 100 switches numbered from 1 to 100. Initially, all the switches are off. The first student presses all the switches so that they are all on. The second student presses every switch that is a multiple of 2 (if the switch is on, it turns off; if it is off, it turns on). The third student does the same for switches that are multiples of 3. This process continues until the 100th student presses switch number 100. After all the students have finished, which switches remain on? Explain your reasoning."

Figure 2. Lamp Problem Task

7. Data Analysis Techniques

This study employs a combination of qualitative and quantitative data analysis methods, using an exploratory case study approach, to gain a comprehensive understanding of how students' computational thinking (CT) influences their ability to solve number pattern problems. In this research, a descriptive analysis of quantitative data collected through problem-solving tasks is used to demonstrate students' competencies in pattern recognition, generalization, and problem solving. At the same time, a qualitative analysis of the data was conducted using thematic analysis. It included an extensive examination of the data set, the coding and identification of relevant themes, and further interpretation in accordance with the concept of computational thinking (CT), including its elements such as decomposition, pattern recognition, abstraction, and algorithmic thinking (Peel, 2020). Triangulation of data sources was used to ensure validity by comparing analyses of written data and interviews (Santos et al., 2020). The percentage of achievements in CT indicators was calculated with the help of the formula:

$$P = \frac{n}{N} \times 100\% \quad (1)$$

Notes:

P = percentage of students meeting the indicator

n = number of students meeting the indicator

N = total number of students

8. Validity and Reliability

The validity and reliability of the study were assessed using four methods. The construct validity was confirmed by extracting all the coding categories from the computational thinking framework, such as decomposition, pattern recognition, abstraction, and algorithmic thinking, based on relevant computational thinking theory (Ngadengon et al., 2024; Wing, 2006). Triangulation of the data sources was conducted by comparing students' test responses with data from the semi-structured interviews to assess the consistency of the computational thinking indicators. Inter-rater reliability was assessed using two independent coders to code students' test answers and interview transcripts according to the same computational thinking indicator rubric.

C. RESULT AND DISCUSSION

This study aims to answer two main questions: (1) how do CT skills support students in solving complex number pattern problems, and (2) which CT indicators contribute most to this process. Data were obtained from two main sources: students' written responses on problem-solving tests and semi-structured interviews with selected students. In addition, the results of the student analysis are presented as a CT indicator diagram, accompanied by descriptive categories for each indicator. These categories are used to describe students' achievement levels and to identify the indicators that contribute most to solving the problems at hand. The percentages of students' CT indicators are presented in Figure 3.

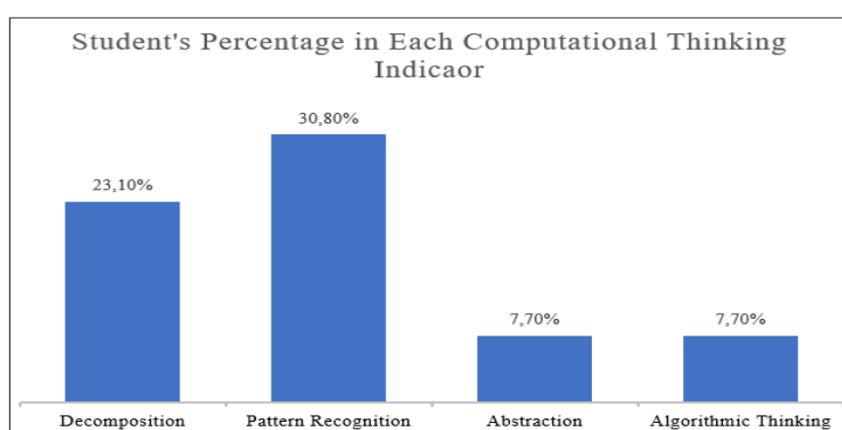


Figure 3. Percentage of CT Ability in Each Indicator

Figure 2 shows that 23.10% of students reached only the decomposition stage, while 30.80% reached the pattern recognition stage. Meanwhile, only a small proportion of students, specifically 7.70%, were able to reach the abstraction and algorithmic thinking stages. This resulted in four interesting findings, one of which is that only a small proportion of students

successfully met all four computational thinking indicators, a group dominated by students with high mathematical ability. This situation indicates that most students still struggle to solve complex problems that require higher-order thinking skills. The description of CT indicators based on students' responses in solving complex number pattern problems is as follows:

1. Decomposition

The first finding shows that 23.10% of students successfully reached the decomposition stage, which involves the ability to break a problem down into smaller parts. For this indicator, students were asked to list the elements they needed to identify in order to solve the problem. The following are student responses demonstrating the decomposition indicator (Figure 4).

SOAL: Di SMP Tirta Bangsa terdapat 100 saklar yang diberi nomor dari 1 hingga 100. Awalnya semua saklar dalam keadaan mati. Siswa pertama menekan semua saklar sehingga semuanya menyala. Siswa kedua menekan setiap saklar bernomor kelipatan 2 (jika saklar menyala, akan mati; jika mati, akan menyala). Siswa ketiga melakukan hal yang sama pada saklar bernomor kelipatan 3. Proses ini berlanjut hingga siswa ke-100 menekan saklar bernomor 100. Setelah semua siswa selesai, saklar mana saja yang tetap menyala? Jelaskan alasannya. Known: The first student presses all switches. The second student presses switches that are multiples of 2, such as 2, 4, 6, 8, and 10. The third student presses switches that are multiples of 3, such as 3, 6, 9, 12, 15, and 18. Asked: Which switches remain on? Method: Student 1: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20 (n) Student 2: 2, 4, 6, 8, 10, 12, 14, 16, 18, 20 (m) Student 3: 3, 6, 9, 12, 15, 18, (n), (m) 4 → 4, 8, 12, 16, 20 m = lamp off 5 → 5, 10, 15, 20 n = lamp on 6 → 6, 12, 18 7 → 7, 14 8 → 8, 16 9 → 9, 18 10 → 10, 20 Conclusion: It seems that only switch number 1 remains on.	Known: The first student presses all switches. The second student presses switches that are multiples of 2, such as 2, 4, 6, 8, and 10. The third student presses switches that are multiples of 3, such as 3, 6, 9, 12, 15, and 18. Asked: Which switches remain on? Method: Student 1: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20 (n) Student 2: 2, 4, 6, 8, 10, 12, 14, 16, 18, 20 (m) Student 3: 3, 6, 9, 12, 15, 18, (n), (m) 4 → 4, 8, 12, 16, 20 m = lamp off 5 → 5, 10, 15, 20 n = lamp on 6 → 6, 12, 18 7 → 7, 14 8 → 8, 16 9 → 9, 18 10 → 10, 20 Conclusion: It seems that only switch number 1 remains on.
--	---

Figure 4. MPA Student's Answer

Based on Figure 4, the MPA student demonstrated their ability to decompose problems by breaking them into smaller parts, as evidenced by their gradual identification of which switches were pressed. On the answer sheets, the MPA student wrote that the first student pressed all the switches, the second pressed them in pairs, and the third pressed them in groups of three. This indicates an effort to simplify a complex problem into a more organised structure, making it easier to analyse. This finding is consistent with the concept of decomposition in CT, which emphasises the ability to break down complex problems into simpler, more manageable sub-problems (Wing, 2006). Furthermore, the MPA student also employed a step-by-step calculation strategy and circled certain numbers to track which switches were pressed repeatedly. These strategies indicate that the students have endeavoured to systematically monitor changes in the switch's state as an initial step in developing an understanding of the emerging pattern. This is consistent with the view of Shute et al. (2017), who state that decomposition helps students organise important information before proceeding to other higher-order thinking processes. It can therefore be concluded that the MPA students have met

the decomposition indicator in solving the set problems. This interpretation is further supported by the interview findings between the researcher (R) and the MPA student, as presented below.

R: "What information did you gather from that problem?"

MPA student: "So, there are 100 switches and 100 students. The first student flips all the switches, the second flips every other switch, the third flips every third switch, and so on."

R: "Why did you write down students 1 through 10?"

MPA student: "Because I was trying to calculate it manually and trying out some quick methods."

R: "What do the circles mean next to those numbers?"

MPA student: "That means the switches will be pressed again by the next student according to the multiples."

R: In your opinion, which switch stays on?"

MPA student: "There is only one switch that stays on, which is switch number 1."

2. Pattern Recognition

The second finding indicates that 30.80% of students are at the pattern recognition stage. At this stage, students can identify patterns in the switch's state changes but still struggle to proceed to the next stage, resulting in incomplete answers (Figure 5).

The figure shows a handwritten student answer for a problem involving 100 switches and 100 students. The answer is divided into two main sections: "Decomposition" and "Pattern Recognition".

Decomposition: This section contains a list of numbers from 1 to 100, written in a grid-like format. The numbers are: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100.

Pattern Recognition: This section contains a table of switch states for 7 switches. The table is as follows:

Switch	State
Switch 1	1 (nyala)
Switch 2	1, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20 (nyala)
Switch 3	1, 3, 6, 9 (mati)
Switch 4	1, 4, 8, 12 (mati)
Switch 5	1, 5, 10, 15, 20 (nyala)
Switch 6	1, 2, 6, 12, 16 (mati)
Switch 7	1

Below the table, the student lists the state of each switch (lamp on/off) for switches 1 through 7:

- Switch 1 → 1 (lamp on)
- Switch 2 → 1, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20 (lamp on)
- Switch 3 → 1, 3, 6, 9 (lamp off)
- Switch 4 → 1, 4, 8, 12 (lamp on)
- Switch 5 → 1, 5, 10, 15, 20 (lamp on)
- Switch 6 → 1, 2, 6, 12, 16 (lamp off)
- Switch 7 → 1

Figure 5. KAS Student's Answer

Based on Figure 5, KAS students have demonstrated indicators of decomposition, characterised by an effort to break down the problem into smaller parts. This is evident from the way the student analysed the switches pressed by each student, starting with switch 1 and proceeding to switch 7, in accordance with the established rules. The KAS student did not immediately tackle all 100 switches, but first simplified the problem to a smaller scale to make it easier to analyse. This strategy demonstrates an effort to reduce problem complexity by simplifying information, a key characteristic of the decomposition indicator in CT (Wing, 2006). Furthermore, the KAS students began to demonstrate the pattern recognition indicator by marking the switch numbers to identify changes in state and noting the final state of the switches based on the pressing sequence performed. This is in line with Chan et al. (2021), who state that pattern recognition plays a crucial role in helping students identify relationships between pieces of information and discover regularities in mathematical problem-solving. However, the student still exhibited inconsistency in determining the final result. This was evident in their answers when determining the switch's final state (on/off). This suggests that although the student was able to identify initial patterns, they still struggled to maintain consistency in these patterns to arrive at accurate generalisations (Cui et al., 2023). It can therefore be concluded that the KAS student demonstrated the ability to meet the indicators of decomposition and pattern recognition when answering the set of problems. This conclusion is further supported by the findings from interviews conducted by the Researcher (R) with KAS students, presented below.

R: "Why did you only list the switches up to switch 7?"

KAS student: "Because it was too long (the number was too big), so I simplified it to make it easier."

R: "What do the strikethroughs on those numbers mean?"

KAS student: "Because they're multiples."

R: "How do you determine whether those switches are on or off?"

KAS student: "From the changes when they're pressed for example, on then off, then on again, and so on."

R: "In your opinion, which switches stay on?"

KAS student: "There are several possibilities, such as switches one and four, or one and five."

3. Abstraction and Algorithmic Thinking

The third finding is that only a small proportion (7.70%) of students successfully reached the final stage of CT, namely the abstraction and algorithmic thinking stage. The students had completed the problem-solving process by fully applying the four stages of CT. At this stage, students were able to generalize the problem into a more general form and systematically formulate solution steps (Figure 6).

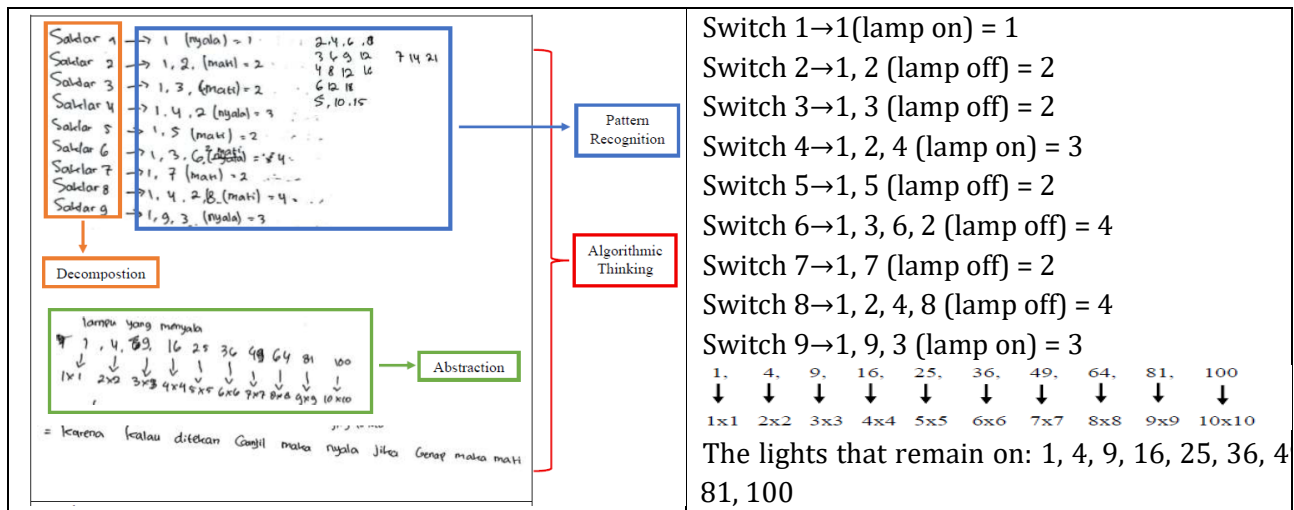


Figure 6. MJH Student's Answer

As shown in Figure 6, MJH students have demonstrated excellent CT skills across all four indicators. At the decomposition stage, the MJH student simplified the problem by analysing switches 1-9 to make it easier to observe. Furthermore, at the pattern recognition stage, MJH students identified that the final state of the switches depended on the number of presses: the switch would turn on if pressed an odd number of times and turn off if pressed an even number of times. At the abstraction stage, MJH student generalised their findings by stating that the switches that are on correspond to perfect squares such as 1, 4, 9, 16, and so on, and represented this in the form of multiplication. This ability demonstrates that students are not only able to recognise patterns but also to filter out important information and construct more abstract mathematical generalisations (Ye et al., 2023).

Furthermore, at the algorithmic thinking stage, MJH students devised a sequential set of steps to solve the problem, starting from observing simple cases, identifying multiples and factors, and ending with systematically determining the switch's final state. It can therefore be concluded that the MJH student demonstrated the ability to meet the decomposition indicators in answering the set problems. This conclusion is further supported by the findings from interviews conducted by the researcher (R) with the MJH student, which are presented below.

R: "How did you start working on this problem?"

MJH student: "I started with the smaller switches first, like switches 1 through 9, so it would be easier to observe."

R: "How did you determine whether a switch was on or off?"

MJH student: "Based on the number of students who pressed the switch; after counting, I found that if it was pressed an odd number of times, it turned on, and if it was pressed an even number of times, it turned off."

R: "How were you able to determine which switch would be on next, like switch 16?"

MJH student: "Because I saw the pattern from 1×1 , 2×2 , 3×3 , so I continued to 4×4 up to 10×10 ."

4. Discussion

Based on the research findings, these results directly address the first research question about how computational thinking (CT) skills help students solve complex number-pattern problems. This can be seen through the process of identifying key information, breaking problems down into simpler parts, and recognising the patterns that emerge. However, this role has not yet been fully realised, as the majority of students are only able to reach the stages of decomposition and pattern recognition, whilst only a small proportion have successfully demonstrated all four CT indicators. This situation indicates that students have been able to identify key information and break problems down into simpler parts, but still face difficulties in progressing to higher-level stages, namely abstraction and algorithmic thinking. In other words, students are relatively capable of initiating the problem-analysis process. However, they are not yet fully prepared to transform the patterns they have discovered into general rules or to devise systematic solution procedures. These findings suggest that secondary students' CT skills in solving complex number-pattern problems are still dominated by basic problem-analysing skills, whilst advanced skills need further development. This is in line with Wing (2006), who explains that CT comprises several interrelated cognitive processes, meaning that each component may develop at a different level in each student.

Furthermore, the findings of this study also answer the second research question, revealing that the most dominant CT indicators were decomposition and pattern recognition. This indicates that students find it easier to break down problems into smaller parts and to identify patterns in the given number sequences. These findings are consistent with those of Aminah et al. (2022), who demonstrated that when solving mathematical problems, students tend to first decompose the problem before identifying patterns. Furthermore, Chan et al. (2023) emphasise that decomposition and pattern recognition are the main foundations for the development of CT, as both play crucial roles in helping students understand a problem's structure. Conversely, the indicators of abstraction and algorithmic thinking emerged in only a small proportion of students, suggesting that students still face difficulties in formulating generalisations of patterns and in designing systematic solution steps. This situation indicates that the transition towards formal generalisation remains a challenge for secondary school students. This is consistent with the findings of Pinto et al. (2022), who demonstrated that students' ability to recognise patterns is not always accompanied by the ability to generalise those patterns into more formal mathematical rules.

Researchers suspect that this situation arises because students are more accustomed to working on routine problems that emphasise direct procedures, rather than on complex problems that require exploration, reasoning, and the generalisation of patterns. The habit of working on routine problems means that students tend to break problems down into smaller parts, but are not yet accustomed to continuing the thought process towards formulating a general model or a systematic solution. This is in line with Jonassen (2000), who emphasises that solving complex problems requires higher-order thinking processes involving in-depth analysis, inference and decision-making. The complexity of mathematical problems often also demands the ability to model situations mathematically, which remains a challenge for many students (Jupri et al., 2016; Verschaffel et al., 2020). Furthermore, Sullivan et al. (2013) explain that effective mathematics learning must involve tasks that encourage students to make

decisions, connect ideas, plan strategies, and explain the reasoning behind their thinking, rather than merely applying memorised procedures. These findings are also supported by Knutson et al. (2025), who demonstrate that the development of generalisation and algorithmic skills requires learning activities that demand reflection, deep reasoning, and metacognitive engagement.

Moreover, the results show that there is a certain group of students with strong mathematical skills who have not developed all stages of computational thinking (CT) effectively. It means that CT does not always evolve in a linear way according to students' mathematical abilities. The conclusion made above is consistent with Lv et al. (2023) who found that although CT activities may improve the overall level of mathematical skills of students, it does not occur uniformly in all areas. In turn, Lee et al. (2023) state that CT is a particular problem-solving strategy which differs from the general mathematical ability. Thus, students with higher mathematical abilities do not have higher CT skills automatically. In other words, the findings made in this research show that there are other aspects besides the level of mathematical skills which influence CT development significantly (Chan et al., 2023). In particular, the main contribution of this research is the demonstration of the way how CT skills, including abstraction and algorithmic thinking, are unevenly developed in students with various mathematical abilities.

In general, the results of this research suggest that computational thinking (CT) is not only a supplementary skill that comes from computer science but rather an intrinsic thinking process involved in mathematical operations. In this case, the teaching of mathematics should include more complicated number pattern questions in order to stimulate deep thinking of learners. Moreover, teachers can scaffold students' thinking using guiding questions, visuals, collaboration, and problem progression from easy to difficult (Puntambekar, 2022). Besides, systematic and regular inclusion of CT exercises in mathematics classes can contribute to improvement of mathematical skills (Dahshan & Galanti, 2024; Nordby et al., 2022). Therefore, the inclusion of complicated problems along with suitable scaffolding can lead to the enhancement of CT skills among lower secondary school students when solving complicated number-pattern problems.

This study makes both theoretical and practical contributions to the development of CT research in mathematics education. Theoretically, this study broadens our understanding of how CT skills develop in the context of solving complex number-pattern problems and demonstrates that the development of CT abilities does not always follow a linear trajectory in relation to students' mathematical ability. In practical terms, the findings of this study can serve as a basis for teachers to design more effective learning strategies to develop CT skills, particularly in abstraction and algorithmic thinking. This study makes a theoretical and practical contribution to the development of CT research in mathematics education. Theoretically, this study broadens our understanding of how CT skills develop in solving problems involving complex number patterns and demonstrates that the development of CT abilities does not always progress linearly with students' mathematical ability. In practical terms, the findings of this study can serve as a basis for teachers to design more effective learning strategies to develop CT skills, particularly in abstraction and algorithmic thinking.

D. CONCLUSION AND SUGGESTIONS

This study shows that CT skills play a key role in helping secondary school students solve complex number pattern problems. The results reveal that the most prominent indicator was pattern recognition, followed by decomposition, whilst abstraction and algorithmic thinking remained at a lower level. This suggests that the majority of students were able to recognise apparent regularities and simplify the problem context, but still experienced difficulties in generalising patterns into formal mathematical representations and devising systematic solution procedures. Furthermore, strong abilities in mathematics cannot always predict strong abilities in CT; hence, these skills do not always develop alongside mathematical skills. This finding supports the assertion that CT must be viewed not only as a technological skill but also as a type of reasoning necessary for problem solving. In terms of future studies, the use of bigger sample sizes is needed in order to test the generalizability of this study's results. Further studies are also needed to test effective instructional approaches which will develop students' skills in abstract and algorithmic reasoning. Thus, CT can be viewed as an innovative approach in education which not only helps students to solve complex number pattern problems but also provides them with necessary reasoning skills for mathematics in today's age.

ACKNOWLEDGEMENT

The author wishes to thank all those who have aided in carrying out this research. Gratitude is particularly owed to the organizations that helped throughout the research exercise, as well as to the subjects who readily participated in the research. The author also thanks the various people whose guidance and suggestions were instrumental in conducting this research.

REFERENCES

- Adeoye-Olatunde, O. A., & Olenik, N. (2021). Research and Scholarly Methods: Semi-structured Interviews. *Department of Pharmacy Practice Faculty Publications*, 1–72. <https://doi.org/10.1002/jac5.1441>
- Adhikari, R., & Timsina, T. P. (2024). An Educational Study Focused on the Application of Mixed Method Approach as a Research Method. *OCEM Journal of Management, Technology & Social Sciences*, 3(1), 94–109. <https://doi.org/10.3126/ocemjmtss.v3i1.62229>
- Aminah, N., Sukestiyarno, Y. L., Wardono, W., & Cahyono, A. N. (2022). Computational Thinking Process of Prospective Mathematics Teacher in Solving Diophantine Linear Equation Problems. *European Journal of Educational Research*, 11(3), 1495–1507. <https://doi.org/10.12973/eu-er.11.3.1495>
- Amri, S., Budiyanto, C. W., & Yuana, R. A. (2019). Beyond computational thinking: Investigating CT roles in the 21st century skill efficacy. *AIP Conference Proceedings*, 2194, 1–8. <https://doi.org/10.1063/1.5139735>
- Apriandi, D., Retnawati, H., & Abadi, A. M. (2023). How Computational Thinking Skills Students in Solving Problems on Pattern Numbers? *AIP Conference Proceedings*, 2595, 1–7. <https://doi.org/10.1063/5.0123713>
- Asbar, V., Asma, N., & Husna, A. (2026). Computational Thinking Ability as the Foundation for Solving Contextual Mathematical Problems among Informatics Students. *Journal Of Informatics, Education and Management (JIEM)*, 8(1), 897–904. <https://doi.org/10.61992/jiem.v8i1.280>
- Astuti, A., Suryawati, E., Suanto, E., Yuanita, P., & Noviana, E. (2025). Charting a course: Exploring computational thinking skills in statistics content among junior high school students. *Journal of Pedagogical Research*, 9(1), 182–202. <https://doi.org/10.33902/JPR.202531653>

- Cahdriyana, R. A., & Richardo, R. (2020). Computational Thinking in Teacher Education. In *Emerging Research, Practice, and Policy on Computational Thinking*. Springer International Publishing, 205-220. https://doi.org/10.1007/978-3-319-52691-1_13
- Chan, S. W., Looi, C. K., Ho, W. K., Huang, W., Seow, P., & Wu, L. (2021). Learning number patterns through computational thinking activities: A Rasch model analysis. *Heliyon*, 7(9), 1-14. <https://doi.org/10.1016/j.heliyon.2021.e07922>
- Chan, S. W., Looi, C. K., Ho, W. K., & Kim, M. S. (2023). Tools and Approaches for Integrating Computational Thinking and Mathematics: A Scoping Review of Current Empirical Studies. *Journal of Educational Computing Research*, 60(8), 2036-2080. <https://doi.org/10.1177/07356331221098793>
- Costa, J. (2024). Mixed Methods in Educational Large-Scale Studies: Integrating Qualitative Perspectives into Secondary Data Analysis. *Education Sciences*, 14(12), 1-13. <https://doi.org/10.3390/educsci14121347>
- Cui, Z., Ng, O., & Jong, M. S. (2023). Integration of Computational Thinking with Mathematical Problem-based Learning Integration of Computational Thinking with Mathematical Problem-based Learning: Insights on Affordances for Learning. *Educational Technology & Society*, 26(2), 131-146. <https://doi.org/10.2307/48721001>
- Dahshan, M., & Galanti, T. (2024). Teachers in the Loop: Integrating Computational Thinking and Mathematics to Build Early Place Value Understanding. *Education Sciences*, 14(2), 1-19. <https://doi.org/10.3390/educsci14020201>
- Firdaus, A. Q., Suryanti, S., & Hadi, F. N. (2026). Identification of Computational Thinking Patterns in Students Mathematical Problem Solving: Empirical Evidence from Algebra Learning Activities. *Jurnal Riset Pendidikan Dan Inovasi Pembelajaran Matematika (JRPIPM)*, 10(1), 22-32. <https://doi.org/10.26740/jrpipm.v10n1.p22-32>
- Golding, J., & Ince, A. (2024). *Ethical Issues in Researching Higher Education Teaching and Learning*. 4(3), 1147-1162. <https://doi.org/10.3390/encyclopedia>
- Helsa, Y., Juandi, D., & Turmudi. (2023). Computational Thinking Skills Indicators in Number Patterns. *Mathematics Education Journal*, 17(2), 167-188. <https://doi.org/10.22342/jpm.17.2.20042.167-188>
- Iskandar, R. S. F., Darhim, D., Dahlan, J. A., & Jupri, A. (2025). Student's Learning Difficulties On Mathematical Understanding Of A Number Pattern. *AKSIOMA: Jurnal Program Studi Pendidikan Matematika*, 14(1), 199-210. <https://doi.org/10.24127/ajpm.v14i1.9677>
- Jonassen, D. H. (2000). Toward a design theory of problem solving. *Educational Technology Research and Development*, 48(4), 63-85. <https://doi.org/10.1007/BF02300500>
- Jupri, A., & Drijvers, P. (2016). Student difficulties in mathematizing word problems in Algebra. *Eurasia Journal of Mathematics, Science and Technology Education*, 12(9), 2481-2502. <https://doi.org/10.12973/eurasia.2016.1299a>
- Knutson, J., & Stagg, K. (2025). The Impact of Teaching Computational Thinking on the Growth of Students Algebraic Thinking. *International Journal of Education in Mathematics, Science and Technology*, 13(6), 1615-1631. <https://doi.org/10.46328/ijemst.5213>
- Lee, I., Grover, S., Martin, F., Pillai, S., & Malyn-Smith, J. (2020). Computational Thinking from a Disciplinary Perspective: Integrating Computational Thinking in K-12 Science, Technology, Engineering, and Mathematics Education. *Journal of Science Education and Technology*, 29(1), 1-8. <https://doi.org/10.1007/s10956-019-09803-w>
- 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), 1-16. <https://doi.org/10.1186/s40594-023-00455-2>
- Lodi, M., & Martini, S. (2021). Computational Thinking, Between Papert and Wing. *Science and Education*, 30(4), 883-908. <https://doi.org/10.1007/s11191-021-00202-5>
- Lv, L., Zhong, B., & Liu, X. (2023). A literature review on the empirical studies of the integration of mathematics and computational thinking. *Education and Information Technologies*, 28(7), 8171-8193. <https://doi.org/10.1007/s10639-022-11518-2>

- Maula, N. F., Suryadi, D., & Jupri, A. (2024). Learning obstacles in the generalization process: In case number pattern topic. *Research and Development in Education (RaDeN)*, 4(2), 964–976. <https://doi.org/10.22219/raden.v4i1>
- Maulina, A. A., & Khusna, H. (2024). *Analysis of Computational Thinking Skills of Vocational School Students Based on Mathematical Literacy Skills in the Society 5.0 Era*. 9(1), 102–120. <https://doi.org/10.33541/edumatsains>
- Mulligan, J., & Mitchelmore, M. (2009). Awareness of Pattern and Structure in Early Mathematical Development. *Mathematics Education Research Journal*, 21(2), 33–49. <https://doi.org/10.1007/BF03217544>
- Ngadengon, Z., Subramaniam, T. S., Yasak, Z., Syukri, M., & Hazim, M. N. (2024). Theory On Computational Thinking In Education: A Systematic Review. *International Journal of Education, Psychology and Counseling*, 9(53), 488–507. <https://doi.org/10.35631/IJEPC.953037>
- 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>
- Palop, B., Díaz, I., Rodríguez-Muñoz, L. J., & Santaengracia, J. J. (2025). Redefining computational thinking: A holistic framework and its implications for K-12 education. *Education and Information Technologies*, 30(10), 13385–13410. <https://doi.org/10.1007/s10639-024-13297-4>
- Peng, J., Hao, M., Chen, B., & Wang, M. (2025). Cultivating computational thinking in a STEM course through the ICDCO instructional model. *Education and Information Technologies*, 30(17), 25137–25175. <https://doi.org/10.1007/s10639-025-13716-0>
- Peracaula-Bosch, M., & González-Martínez, J. (2024). Towards a Hermeneutics of Computational Thinking in Wing's Approximations. *Journal of Educational Computing Research*, 61(8), 139–158. <https://doi.org/10.1177/07356331231193142>
- Pinto, E., Cañadas, M. C., & Moreno, A. (2022). Functional Relationships Evidenced and Representations Used by Third Graders Within a Functional Approach to Early Algebra. *International Journal of Science and Mathematics Education*, 20(6), 1183–1202. <https://doi.org/10.1007/s10763-021-10183-0>
- Puntambekar, S. (2022). Distributed Scaffolding: Scaffolding Students in Classroom Environments. *Educational Psychology Review*, 34(1), 451–472. <https://doi.org/10.1007/s10648-021-09636-3>
- Purwasih, R., Turmudi, & Dahlan, J. A. (2024). How do you solve number pattern problems through mathematical semiotics analysis and computational thinking? *Journal on Mathematics Education*, 15(2), 403–430. <https://doi.org/10.22342/jme.v15i2.pp403-430>
- Rabillas, A. R., Kilag, O. K. T., Cañete, N. A., Trazona, M. S., Calope, M. L. L., & Kilag, J. N. (2024). Elementary Math Learning Through Piaget's Cognitive Development Stages. *International Multidisciplinary Journal Of Research For Innovation, Sustainability and Excellence (IMJRIS)*, 1(9), 202–2010. <https://risejournals.org/index.php/imjrise/article/view/678>
- Rott, B., Specht, B., & Knipping, C. (2021). A descriptive phase model of problem-solving processes. *ZDM - Mathematics Education*, 53(4), 737–752. <https://doi.org/10.1007/s11858-021-01244-3>
- Shute, V. J., Sun, C., & Asbell-Clarke, J. (2017). Demystifying Computational Thinking. *Educational Research Review*, 22, 142–158. <https://doi.org/10.1016/j.edurev.2017.09.003>
- Subramaniam, S., Maat, S. M., & Mahmud, M. S. (2022). Computational thinking in mathematics education: A systematic review. In *Cypriot Journal of Educational Sciences*. Birlesik Dunya Yenilik Arastirma ve Yayincilik Merkezi, 17(6), 2029–2044. <https://doi.org/10.18844/cjes.v17i6.7494>
- Sullivan, P., Clarke, D., & Clarke, B. (2013). Teaching with Tasks for Effective Mathematics Learning. In *Teaching With Task For Effective Mathematics Learning*. Springer Science & Business Media, 9, 1–201. <https://doi.org/10.1007/978-1-4614-4681-1>
- Susanti, R. D., & Taufik, M. (2021). Analysis of Student Computational Thinking in Solving Social Statistics Problems. *SJME (Supremum Journal of Mathematics Education)*, 5(1). <https://doi.org/10.35706/sjme.v5i1.4376>
- Taherdoost, H. (2016). Sampling Methods in Research Methodology; How to Choose a Sampling Technique for Research. In *International Journal of Academic Research in Management (IJARM)*, 5(2). <https://doi.org/10.2139/ssrn.3205035>

- Taufik, M., Inam, A., & Susanti, R. D. (2024). Computational thinking in mathematical problem solving: Pattern recognition. *International Journal of Multidisciplinary: Applied Business and Education Research*, 5(3), 791–797. <https://doi.org/10.11594/ijmaber.05.03.05>
- Udvaros, J., Forman, N., & Avornicului, M. S. (2023). Developing computational thinking with microcontrollers in Education 4.0. *International Journal of Advanced Natural Sciences and Engineering Researches*, 4(4), 103–108. <https://doi.org/10.59287/ijanser.2023.7.4.563>
- Verschaffel, L., Schukajlow, S., Star, J., & Van Dooren, W. (2020). Word problems in mathematics education: a survey. *ZDM - Mathematics Education*, 52(1), 1–16. <https://doi.org/10.1007/s11858-020-01130-4>
- Voon, X. P., Wong, S. L., Wong, L. H., Khambari, M. N. M., & Syed-Abdullah, S. I. S. (2022). Developing Computational Thinking Competencies through Constructivist Argumentation Learning: A Problem-Solving Perspective. *International Journal of Information and Education Technology*, 12(6), 529–539. <https://doi.org/10.18178/ijiet.2022.12.6.1650>
- Wilkie, K. J., & Ayalon, M. (2018). Investigating Years 7 to 12 students knowledge of linear relationships through different contexts and representations. *Mathematics Education Research Journal*, 30(4), 499–523. <https://doi.org/10.1007/s13394-018-0236-8>
- Wing, J. M. (2006). Computational Thinking. *Communications of the ACM*, 49(3), 33–35. <https://doi.org/10.1145/1118178.1118215>.
- Wu, T. T., Asmara, A., Huang, Y. M., & Permata Hapsari, I. (2024). Identification of Problem-Solving Techniques in Computational Thinking Studies: Systematic Literature Review. *SAGE Open*, 14(2), 1–20. <https://doi.org/10.1177/21582440241249897>
- Yadav, A., Stephenson, C., & Hong, H. (2017). Computational thinking for teacher education. *Communications of the ACM*, 60(4), 55–62. <https://doi.org/10.1145/2994591>
- Ye, H., Liang, B., Ng, O. L., & Chai, C. S. (2023). Integration of computational thinking in K-12 mathematics education: a systematic review on CT-based mathematics instruction and student learning. In *International Journal of STEM Education*. Springer Science and Business Media Deutschland GmbH, 10(1), 1–26. <https://doi.org/10.1186/s40594-023-00396-w>
- Zhai, X., Chu, X., Wang, M., Tsai, C.-C., Liang, J.-C., & Spector, J. M. (2024). A systematic review of Stimulated Recall (SR) in educational research from 2012 to 2022. *Humanities and Social Sciences Communications*, 11(1), 1–14. <https://doi.org/10.1057/s41599-024-02987-6>