

Mathematical Problem-Solving Ability from the Perspective of the Computational Thinking Approach

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Abstract

Computational thinking is a practical approach to solving mathematical problems that encourages students to think critically, creatively, and systematically. This type of research employs a descriptive, qualitative approach that aims to describe the mathematical problem-solving abilities of grade 9 students from private junior high schools in Malang, with a focus on computational thinking. The subjects of the study consisted of 6 students representing two high categories, two medium categories, and two low categories, based on the results of the mathematics exam. Data collection techniques include documents, such as student learning scores and tests to measure students' computational thinking abilities, as well as interviews to refine the test results. The data were then analysed based on computational thinking indicators, including decomposition, pattern recognition, generalisation, abstraction, and algorithmic thinking. In the final stage, a description of computational thinking-based problem-solving abilities is presented. The results showed that students in the high category met four of the five computational thinking indicators, except for the generalisation indicator. Students in the medium category met all indicators, while students in the low category only met two indicators: pattern recognition and abstraction. This study emphasises the importance of computational thinking in mathematics education, which aims to improve students' problem-solving skills. Further research may explore appropriate instructional models for the development of computational thinking.

Keywords: Mathematical Problem; Problem-Solving; Computational Thinking.

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Abstrak

Berpikir komputasional merupakan pendekatan praktis dalam memecahkan masalah matematika yang mendorong siswa untuk berpikir kritis, kreatif, dan sistematis. Jenis penelitian ini menggunakan pendekatan kualitatif deskriptif yang bertujuan untuk mendeskripsikan kemampuan pemecahan masalah matematika berbasis berpikir komputasional pada siswa kelas IX SMP Swasta di Malang. Subjek penelitian terdiri dari 6 siswa yang mewakili dua kategori tinggi, dua kategori sedang, dan dua kategori rendah, berdasarkan hasil ujian matematika. Teknik pengumpulan data meliputi dokumen, seperti nilai belajar siswa dan tes untuk mengukur kemampuan berpikir komputasional siswa, serta wawancara untuk menyempurnakan hasil tes. Data kemudian dianalisis berdasarkan indikator berpikir komputasional, meliputi dekomposisi, pengenalan pola, generalisasi, abstraksi, dan berpikir algoritmik. Pada tahap akhir, disajikan deskripsi kemampuan pemecahan masalah berbasis berpikir komputasional. Hasil penelitian menunjukkan bahwa siswa dalam kategori tinggi memenuhi empat dari lima indikator berpikir komputasional, kecuali indikator generalisasi. Siswa dalam kategori sedang memenuhi semua indikator, sedangkan siswa dalam kategori rendah hanya memenuhi dua indikator: pengenalan pola dan abstraksi. Studi ini menekankan pentingnya pemikiran komputasional dalam pendidikan matematika, yang bertujuan untuk meningkatkan keterampilan pemecahan masalah siswa. Penelitian lebih lanjut dapat menyelidiki model pembelajaran yang tepat untuk pengembangan pemikiran komputasional.

INTRODUCTION

Mathematics is a crucial field of study, taught at every educational level from elementary school to university, making it a mandatory subject in education (Shao et al., 2020). The importance of mathematics is evident from the evaluation of student learning abilities, as seen in the 2018 PISA study, which revealed that out of 79 countries, Indonesian students ranked 73rd, placing them in the lower category. Generally, the PISA test aims to assess students' abilities to find solutions to problems (Lestari et al., 2020). Therefore, Nur & Kartini (2021) state that many students still do not favour mathematics because it is perceived as difficult, resulting in generally low mathematics proficiency in Indonesia. Hence, it is vital to implement mathematics education for students as a fundamental science that plays an essential role in daily life, such as 1) problem-solving, 2) foundational education, and 3) measurement and analysis. Considering the low achievement of mathematics results, innovative efforts are needed in mathematics learning that can foster interest and improve students' abilities.

Education as the forefront and hope of the nation to produce capable future

generations, must continually adapt to various forms of changes and developments over time, such as the emergence of artificial intelligence in multiple devices we use (Sanusi et al., 2023; Tsopra et al., 2023; Yilmaz & Yilmaz, K., 2023). In 21st-century learning, mathematics plays a vital role in enhancing critical thinking and problem-solving skills. This finding aligns with the objectives of mathematics education as outlined by the National Council of Teacher Mathematics (NCTM), Jamna et al., (2022), which states that mathematics education helps students develop skills in 1) problem-solving; 2) reasoning and proof; 3) communication; 4) connection; and 5) representation. The discussion above highlights that critical thinking and problem-solving abilities are key factors in mathematics education, particularly in the 21st century. Computational thinking is a skill that enables students to think abstractly, algorithmically, and logically, allowing them to solve complex problems. Thus, critical thinking and problem-solving skills have become the primary focus of modern mathematics education that is relevant to global challenges. One relevant approach to developing these skills is through the application of computational thinking.

In addition to these concerns,

computational thinking serves as a metacognitive tool that enables learners not only to engage with content knowledge but also to evaluate their problem-solving strategies. This skill is pivotal in a world increasingly dominated by algorithmic logic and data-driven decision-making. By embedding computational thinking into mathematics education, educators provide students with transferable skills that go beyond the classroom and into everyday reasoning.

Moreover, research by Montuori et al. (2024) found that students exposed to computational thinking instruction exhibited improved analytical reasoning and cognitive flexibility. These competencies are closely tied to success in mathematical problem-solving, as students must be able to adapt their strategies when one approach fails and dynamically reassess their understanding. Thus, the integration of computational thinking within mathematics is not merely about enhancing performance, but also about fostering adaptability and resilience.

While computational thinking is often associated with computer science, its core principles align naturally with mathematical practices. Both domains emphasise pattern recognition, generalisation, Abstraction, and logic, all of which are necessary for modelling real-world problems and reasoning through complex tasks. The synergy between these disciplines provides a fertile ground for enhancing students' critical thinking and analytical capabilities in a more interconnected and meaningful way.

Despite its potential, many teachers continue to struggle with implementing computational thinking strategies effectively. This difficulty is partly due to limited training and lack of curriculum alignment, but also because of a misconception that computational

thinking requires coding or programming tools. In reality, as Bråting and Kilhamn (2021) and Wing (2017) emphasise, computational thinking can be developed through carefully designed mathematical tasks that involve problem decomposition, iterative reasoning, and algorithmic planning, without the need for digital devices.

Consequently, schools and educators must be supported in recognising the broader applications of computational thinking and equipped with the necessary resources to integrate it into their teaching. This educator's support includes the development of learning modules, teacher training programs, and assessment frameworks that reflect computational thinking processes. When students are taught to think like mathematicians and computer scientists simultaneously, their ability to tackle multifaceted problems is significantly enhanced.

In this context, the present study seeks to contribute to the growing body of literature on computational thinking by examining its manifestation in the mathematical problem-solving abilities of ninth-grade students. Focusing specifically on the topic of number patterns and sequences, this study identifies how students with varying levels of achievement apply computational thinking indicators. By doing so, it aims to bridge the theoretical and practical gaps in current mathematics education and offer insights that can inform future instructional practices.

Computational thinking is a skill that enables students to think abstractly, algorithmically, and logically, allowing them to solve complex problems. Novitasari et al. (2017) suggest that certain factors should be considered when engaging in mental activities. Mental activities refer to the thinking processes

that occur in the brain. Argue that the basic objects of mathematics, such as facts, concepts, relationships, and principles, are abstract and thus cannot be fully understood through mere memorisation; instead, a thinking process is required. According to Putria et al. (2020), thinking refers to a cognitive process carried out internally to interpret incoming information and may be inferred through observable actions or behaviors. (Saidah et al., 2019) argue that thinking is an effort to identify and solve problems faced by students. Based on these perspectives, mathematics learning should place a particular emphasis on students' thinking processes. One of the main objectives is to habituate students to process and transform information to solve mathematical problems. Therefore, students need to acquire 21st-century thinking skills, particularly computational thinking. Computational thinking focuses more on the problem-solving process rather than merely on the final result. This focus is a 21st-century educational concept, as explained by experts, which involves understanding and solving complex problems through aspects such as decomposition, pattern recognition, Abstraction, and algorithmic thinking. These four aspects are essential elements in computational thinking.

Wing (2017) argues that by the mid-21st century, computational thinking will become a fundamental skill used by everyone worldwide. This argument is reinforced by Zulfa and Andriyani (2023), who state that computational thinking skills can enhance problem-solving abilities in the 21st century. These skills enable learners to formulate and present well-planned or effectively executed solutions (Bråting & Kilhamn, 2021; Guggemos, 2021; Montuori et al., 2024). Furthermore, Jamna et al. (2022) emphasise that introducing

computational thinking in mathematics classrooms is crucial, as it prepares students for the professional world. In line with this, Celik (2023), Findayani et al. (2023), and Piatti et al. (2022) define computational thinking as a set of thought patterns that involve designing systems utilising computers as a medium or platform to solve problems. Similarly, According to Danindra and Masriyah (2020), computational thinking encompasses mental processes such as problem identification, systematic explanation, multi-level abstraction, and constructing automated solutions. In alignment with this, Stella et al. (2021) characterize computational thinking as students' capacity to recognize patterns, deconstruct intricate problems into manageable components, arrange these elements logically, and represent information using simulations. This understanding is supported by Al-Khateeb (2018) and Supiarmo et al. (2021), who describe computational thinking as a series of abstractions, including Abstraction, decomposition, pattern mapping, testing, and generalisation. (Yuntawati et al., 2021) describe it as a mental process for formulating and developing problems and solutions to ensure their effectiveness. Fundamentally, computational thinking equips learners with the ability to approach problems using abstract, algorithmic, and logical reasoning. It holds significant value in educational contexts, particularly in designing computer-based solutions. Harmini et al. (2020) further note that computational thinking can be developed as a cognitive strategy for resolving problems through the integration of digital tools. However, beyond its technological applications, computational thinking is also highly applicable to problem-solving within mathematics education.

Computational thinking comprises five components: 1) decomposition; 2) pattern recognition; 3) abstraction; 4) generalisation; and 5) algorithms. This framework is supported by Danindra & Masriyah, (2020) who explain the five components of computational thinking as follows: 1) decomposition is the ability to break down information or complex problems into simpler, more manageable parts to enhance understanding; 2) pattern recognition refers to the skill of identifying, analyse, and connecting recurring patterns or relationships among data; 3) algorithmic thinking emphasises the ability to structure and analyse problems logically and to devise step-by-step procedures to reach solutions; and 4) generalisation and Abstraction the ability to extract general principles from specific problems and to simplify complexity by focusing on the essential features of the problem. Together, these five components of computational thinking support students in developing systematic approaches to problem-solving and in constructing effective, logical solutions.

Problem-solving is an essential process in providing solutions based on facts, especially when addressing mathematical problems (Novriani & Surya, 2017; Ramadhan *et al.*, 2021). The study of problem-solving lies at the heart of mathematics education (Wulandari *et al.*, 2023). Through mathematical problem-solving, students can deepen their understanding by applying mathematics to real-life contexts (Rosyada & Wibowo, 2023). Therefore, it can be stated that problem-solving plays a crucial role in the learning of mathematics. One of the key factors influencing students' problem-solving abilities is computational thinking. Several aspects affect students' mathematical problem-solving skills, one

of which is the level of mathematical competence they possess (Sari, L. N., 2016). Computational thinking, in particular, helps students simplify complex problems and construct effective strategies for solving them. According to Budiarti *et al.* (2022), mathematical issues can be more easily addressed when students are accustomed to engaging in computational thinking processes. Moreover, the teacher's role is also critical in shaping students' problem-solving abilities. Teachers play a significant role in guiding students to achieve satisfactory learning outcomes and meet expected learning goals (Manah *et al.*, 2017; Utomo *et al.*, 2021). One effective strategy to accomplish this is by encouraging students to develop solutions to mathematical problems through the use of a computational thinking approach.

Based on a preliminary study conducted in a ninth-grade class at a private junior high school in Malang City, it was found that students' computational thinking abilities were still relatively weak. Classroom observations and interviews with the mathematics teacher supported this finding. During observations, students struggled to identify and continue number patterns, particularly when the sequences involved alternating or recursive rules. For instance, some students failed to recognise the regularity in patterns such as 2, 4, 7, 11, ..., and often applied incorrect operations when determining the following terms. In problems that involved two number sequences progressing in opposite directions, students tended to focus on isolated calculations without fully understanding the relational structure between the sequences.

Another observed issue was students' inability to verify their solutions or check for reasonableness, which is also related to algorithmic thinking. Some

students used trial-and-error methods and abandoned the task when they found no immediate answer. This behaviour highlights not only a lack of perseverance but also inadequate algorithmic planning. In interviews, several students expressed confusion when asked to explain the steps they used to reach a solution, further indicating the need for structured algorithmic thinking to be fostered through instruction. Additionally, students often failed to identify efficient pathways to get solutions, opting instead for repetitive and inefficient calculations that did not guarantee success.

The mathematics teacher also reported that students often struggled to distinguish between the information provided and the information being asked in the problems. Many showed confusion in deciding how to begin. This phenomenon shows a lack of decomposition skills. Moreover, most students did not articulate general conclusions from the patterns they found; they tended to stop once they obtained a numerical result, indicating a weakness in their ability to generalise. These difficulties highlight gaps in core indicators of computational thinking, particularly decomposition, generalisation, and algorithmic reasoning.

Furthermore, the teacher reported that students often struggled to answer similar questions during lessons and required substantial guidance to recall prior knowledge that had already been taught. This suggests that students' problem-solving abilities remain underdeveloped. According to Bilbao et al. (2021) and Wijaya et al. (2024), if students clearly understand the learning objectives, they are more likely to achieve those objectives effectively. Therefore, in response to these findings, there is a need to develop learning models that actively

engage students in constructing knowledge. Such models are expected to improve students' mathematical problem-solving skills (Gunawan et al., 2023; Gyanthi et al., 2023; Yapatang & Polyiem, 2022).

Several previous scholars have explored research on problem-solving skills through the lens of computational thinking. For instance, a study by Budiarti et al. (2022b) examined the relationship between computational thinking and problem-solving skills using number pattern materials at the senior high school level. However, the present study differs in that it focuses on problem-solving abilities through a computational thinking approach in the context of number patterns and sequences at the junior high school level. Another related study by Setyadi et al. (2020) investigated problem-solving abilities from the perspective of students' learning styles, aiming to identify differences in problem-solving performance based on those styles. In contrast, the current study employs a computational thinking perspective to analyse students' mathematical problem-solving skills. The novelty of this research lies in the use of paired tests and paired interviews based on students' problem-solving categories to assess their abilities through computational thinking. Therefore, the purpose of this study is to analyse students' mathematical problem-solving skills through a computational thinking approach.

METHOD

This research is a descriptive study with a qualitative approach, aiming to analyse mathematical problem-solving abilities in the context of number patterns and sequences from the perspective of computational thinking. The study was

conducted with ninth-grade students at a private junior high school in Malang. The subjects consisted of six students, categorised into two high-achieving, two average-achieving, and two low-achieving students. The subjects were selected based on their mathematical problem-solving abilities as observed by their teacher in previous class activities. High-achieving students were included to explore the complete manifestation of computational thinking indicators, as they tend to demonstrate more complex and structured problem-solving strategies. Their inclusion allows for comparison across performance levels and provides insight into the variation in computational thinking skills among students with different levels of achievement.

The data in this study consists of an analysis of participants' mathematical problem-solving abilities in computational thinking. The instruments used include observation for categorising mathematical ability, test questions to measure mathematical problem-solving skills from the perspective of computational thinking, and interviews to delve deeper into participants' problem-solving skills in number patterns and sequences.

The data analysis techniques employed in this research encompass several key aspects, including data collection, data condensation, data analysis, and conclusion. The data collection techniques involved interviews to assess students' mathematical abilities, tests to evaluate their problem-solving skills on the topic of number patterns and sequences based on predetermined indicators, and further interviews to explore the students' conceptual understanding in more depth. The tests used were designed according to computational thinking indicators and

were validated by two experts in mathematics education: one with extensive experience in developing mathematics assessments at the university level, and another who is a certified junior high school mathematics teacher with practical classroom experience in teaching number patterns and sequences.

The indicators of computational thinking used in this study refer to the framework proposed by Danindra and Masriyah (2020), which includes decomposition, pattern recognition, generalisation, Abstraction, and algorithmic thinking. The steps and indicators adapted from their work are summarised in Table 1 below.

Table 1. Steps and Indicators of Computational Thinking

Criteria of Computational Thinking	Indicators
Decomposition	a) Students can determine what needs to be known in problem-solving b) Students can determine what needs to be asked in problem-solving
Pattern Recognition	Students are capable of recognising patterns or characteristics, whether similar or different, to solve the given problem effectively
Generalisation and Abstraction	a) Students can articulate general patterns from similarities or differences identified in the given problem b) Students are capable of concluding from patterns identified in the given problem
Algorithm	Students are capable of enumerating the logical steps used to formulate a solution that has been employed.

The test results will then be analysed based on the indicators outlined in Table 1. The data analysis techniques employed in this research include data collection, data presentation, and conclusion. In the first stage, data collection was conducted using tests, documents, and interviews. The documents collected consisted of students' academic performance records, which were used to categorise their mathematical problem-solving abilities into high, medium, and low categories. The tests in this study were conducted in pairs, with each pair consisting of two students, to assess their mathematical problem-solving abilities based on computational thinking indicators. The tests comprised three questions on number patterns and sequences. Interviews were conducted in pairs using an unstructured interview format, and the data collected included video recordings, field notes, and interview transcripts.

The data analysis in this study followed Miles and Huberman's model, which includes data collection, data condensation, data display, and conclusion drawing. Data collection was carried out through written tests, documentation of learning outcomes, and interviews. In the data condensation stage, student responses were coded and categorised based on five computational thinking indicators: decomposition, pattern recognition, Abstraction, generalisation, and algorithm. The data display stage included a descriptive analysis of the data to describe students' mathematical problem-solving abilities based on their test results, which illustrated the level of their performance in terms of the computational thinking indicator. Furthermore, students' mathematical problem-solving skills could be observed as they engaged with mathematical problems using a

computational thinking approach, allowing the collected data to reflect the connection between computational processes and the problem-solving strategies applied by the students.

In the final stage, conclusions were drawn by interpreting student responses based on their achievement categories—high, medium, and low—to identify patterns across the computational thinking components. To represent the research procedure, the stages of the study are summarised in the following graphic organiser: (1) subject selection based on achievement levels, (2) instrument development and validation, (3) administration of problem-solving tests, (4) interviews, (5) data transcription and coding, (6) categorisation based on computational thinking indicators, (7) descriptive data presentation, and (8) interpretation and conclusion drawing.

RESULT AND DISCUSSION

Results

The discussion that follows is based on research conducted by the researcher during the task completion process. This analysis aims to determine how mathematical problem-solving abilities are viewed through computational thinking. The computational thinking indicators used include decomposition, pattern recognition, Abstraction, generalisation, and algorithms. Presented below are the answers and data analysis from paired interviews within each category.

Table 2. Overview of Computational Thinking Abilities Differences among High, Medium, and Low Categories

Description:

(-) : Does not meet the category

(√) : Meets the category

Criteria of Computational Thinking	Problem-solving abilities		
	High	Medium	Low
Decomposition	√	√	—
Pattern Recognition	√	√	√
Abstraction	√	√	√
Generalisation	—	√	—
Algorithm	√	√	—

Description of Problem-Solving Abilities Based on Computational Thinking in Students with High Proficiency

Based on the results of the high-category subjects' responses in solving all given problems, as depicted in Figure 1, subjects in the high category were able to solve the problems using computational thinking indicators such as decomposition, pattern recognition, Abstraction, and algorithms. However, subjects in the high category were unable to solve using the computational thinking indicator of generalisation. Therefore, it can be stated that subjects in the high category were unable to articulate conclusions from the problems because they had already found answers through their calculations at the end.

Diket: Fachmi: 1008, 1016, 1024, 1032, ...
Zeldy: 2004, 2000, 1996, 1992, ...
Dit: Hitungan angka yang sama?

Jwb: $F = a + (n-1)b$
 $= 1008 + (n-1)8$
 $= 1008 + 8n - 8$
 $= 992 + 8n$

$Z = a + (n-1)b$
 $= 2008 + (n-1)4$
 $= 2008 + 4n - 4$
 $= 2004 + 4n$

Fachmi = Zeldy
 $992 + 8n = 2004 + 4n$
 $8n + 4n = 2004 - 992$
 $12n = 1020$
 $n = \frac{1020}{12}$
 $n = 85$

Jwb: $992 + 8n$
 $= 992 + 8 \cdot 85$
 $= 992 + 680$
 $= 1672$

Known:
 - Fachmi: 1008, 1016, 1024, 1032, ...
 - Zeldy: 2004, 2000, 1996, 1992, ...
 Asked: Count the same numbers?

Answer:

- $F = a + (n-1)b$
 $= 1008 + (n-1)8$
 $= 1008 + 8n - 8$
 $= 1008 - 8 + 8n$
 $= 1000 + 8n$

- $Z = a + (n-1)b$
 $= 2008 + (n-1)4$
 $= 2008 - 4n + 4$
 $= 2004 + 4 - 4n$
 $= 2008 - 4n$

- Fachmi = Zeldy
 $992 + 8n = 2012 - 4n$
 $8n + 4n = 2012 - 992$
 $12n = 1020$
 $n = \frac{1020}{12}$
 $n = 85$

- Fachmi equation:
 $= 992 + 8n$
 $= 992 + 8 \cdot 85$
 $= 992 + 680$
 $= 1672$

Decomposition

Pattern Recognition

Abstraction

Algorithm

Figure 1. Answer to Problems by High Category

There was an interview conducted with the students regarding the indicators that were not fulfilled as follows:

P: Earlier, you worked on the problems and obtained the final results, correct?

S1: Yes, we found it, Miss.

P: So, what about the conclusion from that problem?

S1: The conclusion is that Fahmi and Zeldy both said the number 85 on the 1672.

Based on the interview results, it is understood that the students comprehend the conclusion from solving the problem, namely that Fahmi and Zeldy uttered the same number on the eight counts. However, the students did

not write down the conclusion on the answer sheet because the answer was already represented by the number 1672, which was written as the final calculation result.

Description of Problem-Solving Abilities Based on Computational Thinking in Students with Medium Proficiency

Based on the analysis of responses

Diket: Fachmi berhitung maju mulai dari angka 1000 beraturan 8
Zeldy berhitung mundur mulai dari angka 2008 dgn kelipatan 4

Ditanya: Mengetahui hitungan angka yg sama

Jawab: - Un Fachmi : $a + (n-1)b$
 $= 1000 + (n-1)8$
 $= 1000 + 8n - 8$
 $= 992 + 8n$

- Un Zeldy : $a + (n-1)b$
 $= 2008 + (n-1)(-4)$
 $= 2008 + 4n - 4$
 $= 2004 + 4n$

- U_n Fachmi = U_n Zeldy
 $992 + 8n = 2004 + 4n$
 $8n - 4n = 2004 - 992$
 $4n = 1012$
 $n = \frac{1012}{4} = 253$

Jadi, Fachmi dan Zeldy mengatakan angka yg sama pada hitungan ke-253

from subjects in the medium category in solving all given problems, as depicted in Figure 2, subjects in the medium category were able to solve the problems using computational thinking indicators such as decomposition, pattern recognition, and algorithms. Therefore, it can be concluded that students with medium mathematical proficiency demonstrate strong computational thinking skills.

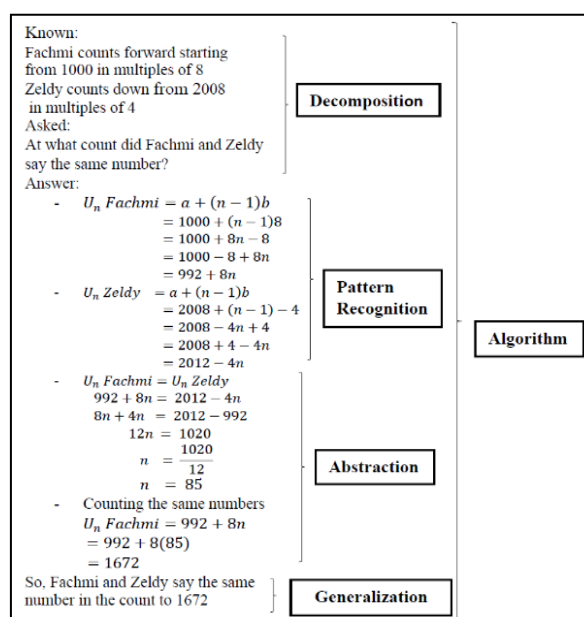


Figure 2. Answer to Problems by Medium Category

There are several excerpts from interviews conducted with students when asked about solving problems as follows:

P: Please explain and identify what is known and what is being asked in the problem that was provided earlier.

S2: It is known that Fachmi counts forward from 1000 in multiples of 8, and Zeldy counts backwards from 2008 in multiples of 4. The question asks at what count Fachmi and Zeldy will say the same number.

P: The method for solving the problem has already been discussed. Could you outline the steps to solve the issue, along with the conclusion?

S2: First, we calculate the values for Fachmi and Zeldy, then find the equation where

their values match, continuing until we arrive at the final answer. The conclusion is that Fachmi and Zeldy will say the same number at count 1672.

Based on the interview results, students in the medium category can be said to have successfully solved the problems accurately, as indicated by computational thinking indicators.

Description of Problem-Solving Abilities Based on Computational Thinking in Students with Low Proficiency

Based on the analysis of responses from subjects in the low category, in completing all given tasks. In Figure 3, subjects in the low category were able to

solve problems using computational thinking indicators such as pattern recognition and Abstraction. However, they have not yet mastered computational thinking indicators such as decomposition, generalisation, and

algorithms. Therefore, it can be said that students with low mathematical abilities in solving problems using computational thinking indicators still require improvement.

The figure displays two columns of handwritten mathematical work, likely from a student's solution to a problem involving arithmetic sequences.

Left Column (Handwritten Solution):

$$\begin{aligned}
 U_n &= a + (n-1)b \\
 1000 + (n-1)8 &= 2008 + (n-1)4 \\
 1000 + 8n - 8 &= 2008 - 4n + 4 \\
 8n + 4n &= 2012 - 992 \\
 12n &= 1020 \\
 n &= \frac{1020}{12} \\
 n &= 85
 \end{aligned}$$

Then, to find U_{85} :

$$\begin{aligned}
 \text{mencari } U_{85} &= a + (n-1)b \\
 U_{85} &= 1000 + (85-1)8 \\
 U_{85} &= 1000 + (84)8 \\
 U_{85} &= 1000 + 672 \\
 U_{85} &= \underline{\underline{1672}}
 \end{aligned}$$

Right Column (Structured Solution):

$$\begin{aligned}
 U_n &= a + (n-1)b \\
 1000 + (n-1)8 &= 2008 + (n-1)4 \\
 1000 + 8n - 8 &= 2008 - 4n + 4 \\
 8n + 4n &= 2012 - 992 \\
 12n &= 1020 \\
 n &= \frac{1020}{12} \\
 n &= 85
 \end{aligned}$$

This section is labeled **Pattern Recognition**.

Then, to find U_{85} :

$$\begin{aligned}
 \text{Look for } U_{85} &= a + (n-1)b \\
 U_{85} &= 1000 + (85-1)8 \\
 U_{85} &= 1000 + (84)8 \\
 U_{85} &= 1000 + 672 \\
 U_{85} &= 1672
 \end{aligned}$$

This section is labeled **Abstraction**.

Figure 3. Answer to Problem by Low Category

There was an interview conducted with the students regarding the indicators that were not fulfilled as follows:

P: Please state what is known and what is being asked in the problem that was provided earlier.

S₃: It is known that Fachmi counts forward from 1000 in multiples of 8, and Zeldy counts backwards from 2008 in multiples of 4. The question asks at what count Fachmi and Zeldy will say the same number.

P: How did you determine the steps to solve the problem and reach the conclusion?

S₃: To find the count where Fachmi and Zeldy have the same number, we denote $a = 1000$ and $b = 8$ for Fachmi, and $a = 2008$ and $b = 4$ for Zeldy. By solving using the formula $U_n = a + (n-1)b$, we arrive at the final result. The conclusion is that the count, as stated by Fachmi and Zeldy, is 1672.

Based on the conducted interview, it appears that the students understand what was known, what was asked, what

was concluded, and the steps taken in solving the problem, specifically with the values a as 1000 and b as 8. They proceeded to calculate $1000 + (n - 1.8) = 2008 + (n - 1.4)$, resulting in $n = 85$. Thus, resulting U_{85} as 1672. However, the students did not document what was known, what was concluded, and the steps taken in solving the problem because they used manual calculations and had already obtained the final result.

Discussion

The initial steps taken by students when solving problems include understanding the problem statement, documenting what is known and what is being asked, planning the solution, implementing the devised strategies, and finally drawing conclusions. Based on the research findings, it was found that high-achieving students were able to meet four computational thinking indicators while working on all the problems. They

successfully addressed the computational thinking indicators of decomposition, pattern recognition, abstraction, and algorithm. However, they did not fulfil the final indicator, generalisation. They fulfilled decomposition by identifying and stating what was known and what was asked in the problems, both in their written answers and during interviews. In pattern recognition, they observed numerical sequences (e.g., increasing by eight or decreasing by 4) and used these patterns to search for matching values. Their abstraction skills appeared in how they translated real-world problem statements into mathematical representations, although not all abstractions were explicitly stated. For the algorithmic indicator, they demonstrated the ability to apply clear step-by-step procedures to arrive at correct results. However, for generalisation, the students did not write concluding statements or express generalised patterns, even though they understood the result; they perceived that reaching the correct answer was sufficient, as confirmed in interviews. These research findings are consistent with those of Fikriyah (2022) and Anggriani (2023), indicating that high-achieving students in mathematics only satisfy four computational thinking indicators, with the remaining indicator, generalisation, deemed unnecessary by the students.

Students categorised as moderate were able to fulfil all five computational thinking indicators while working on all problems. They demonstrated decomposition by clearly stating the known information and identifying what was being asked in each issue, both in their written responses and during interviews. For pattern recognition, they were able to observe and analyse arithmetic patterns in the sequences and

used this understanding to predict the correct results. In terms of Abstraction, students interpreted the real-world context of the problems and translated them into mathematical models using variables and equations. The generalisation indicator was fulfilled by drawing explicit conclusions from the results obtained, for example, by stating at what point two sequences intersected and articulating the reasons why. Lastly, their algorithmic thinking was evident in their ability to outline and follow logical, step-by-step procedures to reach a solution. This comprehensive application of all five indicators reflects a strong integration of computational thinking in their problem-solving process. This research outcome contrasts with that of Fikriyah (2022) and Anggriani (2023). Students categorised as moderate were able to fulfil all five computational thinking indicators while working on all problems. This research outcome contrasts with that of Fikriyah (2022) and Anggriani (2023), where students with moderate abilities did not satisfy all computational thinking indicators, notably algorithm and generalisation, in the context of solving systems of linear equations. This discrepancy may be attributed to the higher level of algorithmic complexity required to solve linear systems compared to number patterns and sequence problems. The findings are consistent with those of Nuraini et al. (2023), who also found that students in the moderate category struggled with algorithm and generalisation indicators. Another factor contributing to the different outcomes is the categorisation method. This study used daily assessments and mid-term exam results to classify student ability levels, whereas previous studies relied solely on pre-test performance.

Students with low mathematical

problem-solving abilities, while working on all problems, only fulfilled two computational thinking indicators: pattern recognition and abstraction. In terms of pattern recognition, they were able to identify basic numerical patterns, such as consistent additions or subtractions in sequences. However, they sometimes relied on guesswork rather than systematic analysis. Their ability in Abstraction was shown by how they represented real-life situations into simple mathematical expressions, even though the formulation was not always complete. However, they did not meet the decomposition indicator, as they were unable to state what was known and what was being asked clearly. This was evident both in their written responses and in interview transcripts, where they appeared confused or hesitant. The generalisation indicator was also not fulfilled, since they did not draw conclusions or articulate the meaning of their findings within a broader context. Once they obtained a numerical result, they did not reflect on it further. Moreover, their algorithmic thinking was weak, as they did not follow structured steps or a consistent strategy in solving problems; instead, their work showed trial-and-error attempts without logical sequencing. These research findings align with those of Fikriyah (2022) and Anggriani (2023), which state that students with low mathematical abilities often struggle to fulfil two indicators of computational thinking because they find the problems difficult and are unable to complete them. However, in this study, paired interviews revealed that the students worked together without being prompted to revise or evaluate their answers, suggesting that their discussion process was active and collaborative. The researcher noted that this may have been influenced by the fact that both students

in the low category were male, which potentially affected their interaction dynamics.

Based on the students' responses, it is evident that students who consistently applied the first to the second indicators included those in the high, medium, and low categories. In contrast, those who used the third indicator included those in the high and medium categories. For the fourth indicator, it was applied by students in the high and medium categories. Thus, the fifth indicator was applied by students in the medium category, while students in the high and low categories did not meet the generalisation indicator, specifically, the conclusion. This indicates that only the medium category has maximised problem-solving by computational thinking indicators. In contrast, students in the high and low categories have not yet maximised problem-solving according to computational thinking indicators.

These findings align with Wing's (2017) conceptualisation of computational thinking as a vital skill across disciplines. In particular, the fact that students with moderate mathematical achievement were able to fulfil all five indicators suggests that computational thinking is not only associated with high academic performance. Instead, it indicates that students who are trained or guided through structured reasoning and problem breakdown can exhibit strong problem-solving capabilities regardless of their prior mathematical achievement. This highlights that instructional support and task design play crucial roles in fostering computational thinking skills.

The difference in performance across high, medium, and low categories can also be interpreted through Vygotsky's Zone of Proximal Development (ZPD). Students in the

moderate group likely benefited from cognitive scaffolding during peer discussions or instructional support that helped them extend their reasoning capabilities (Chou et al., 2024). This underscores the importance of collaborative learning environments in fostering computational thinking within mathematical problem-solving tasks.

Furthermore, these results reflect broader implications for curriculum design. This study demonstrates that computational thinking is not limited to programming environments (Zaibon & Yunus, 2019). When computational thinking is effectively integrated into mathematical problems, such as number patterns and sequences, students are encouraged to move beyond rote procedures and engage in deeper, more strategic thinking. Therefore, educators and curriculum developers should integrate computational thinking indicators into both instructional materials and assessment tools.

Several previous studies reinforce these findings. Fikriyah (2022) found that students often neglect the generalisation indicator, focusing instead on arriving at correct answers. This finding is consistent with the current study, in which high-achieving students frequently failed to state generalisations, feeling that a numerical answer alone was sufficient. In contrast, Montuori et al. (2024) emphasised that generalisation is a key component of computational thinking and should be cultivated explicitly through instruction.

Similarly, Bråting & Kilhamn (2021) observed that Abstraction and generalisation are frequently underdeveloped unless intentionally taught. The fact that only students in the moderate category fulfilled all indicators in this study supports their conclusion. This further underscores the need to

teach these indicators explicitly in the context of mathematical problem-solving.

Methodologically, the use of paired testing and interviews in this study provided more profound insights into how students approach problem-solving. Unlike written tests alone, the interviews allowed students to verbalise their reasoning, clarify their thought processes, and reflect on the logic behind their answers. This qualitative approach proved effective in revealing how students engaged with each computational thinking indicator in real time.

These insights have practical implications for teacher training. If teachers are better equipped to recognise and foster computational thinking, particularly decomposition and generalisation, they can more effectively support students across all performance levels. This study also showed that even students with low mathematical abilities were able to demonstrate Abstraction and pattern recognition, suggesting that with proper guidance, they too can develop the other indicators over time.

Implication of Research

This research aims to assess students' mathematical problem-solving abilities through the lens of computational thinking as they engage with mathematical problems. By recognising students' problem-solving skills from the perspective of computational thinking, teachers can gain a better understanding of the individual needs and challenges students face when addressing mathematical problems. Moreover, this research demonstrates that mathematical problem-solving abilities can be analysed through the computational thinking approach, aiding in the development of more effective and

precise problem-solving strategies. Teachers can categorise students into high, medium, and low categories, allowing them to accommodate the differing characteristics of these groups when solving mathematical problems. Adjusting lesson plans to align with students' computational thinking abilities will help enhance their understanding and critical thinking skills in mathematics, particularly in the study of number patterns and sequences.

Limitation

This research specifically examines students' mathematical problem-solving skills from the perspective of computational thinking, with a focus on number patterns and sequences in a ninth-grade classroom at a private junior high school in Malang. Due to the limited participant pool and contextual specificity, the findings may not be widely generalizable. Nonetheless, as a qualitative inquiry, the study seeks to offer nuanced perspectives on how computational thinking emerges during students' problem-solving in mathematics.

Additionally, the research addresses a conceptual void in existing scholarship, as much of the prior work has explored computational thinking within computer science and programming domains. Wing (2017), for instance, underscored its relevance as a core 21st-century competency, although her framework leaned heavily on computing and scientific exploration. Likewise, Celik (2023) emphasized computational thinking's significance in advancing digital literacy and AI understanding, yet his research remained rooted in technologically oriented disciplines rather than in mathematics instruction.

This study contributes to the field

by explicitly applying computational thinking in the context of mathematics learning, particularly in analysing students' reasoning when solving number pattern problems. It provides empirical evidence of how students with different levels of problem-solving ability engage with decomposition, pattern recognition, Abstraction, generalisation, and algorithmic thinking. Despite its limited scope, the findings offer meaningful contributions to both mathematics education and computational thinking research by demonstrating how these indicators can be observed and analysed in real classroom situations.

CONCLUSION

Based on the research findings, it can be concluded that the ability to solve mathematical problems, as viewed through the computational thinking approach in the material of number patterns and sequences for Grade IX students at a private junior high school in Malang, still needs further improvement. The results obtained are as follows: 1) students in the high category can fulfil four computational thinking indicators, but they did not fulfill the fifth indicator, generalisation, in the three given problems; 2) students in the medium category were able to fulfill all computational thinking indicators in all given problems; and 3) students in the low category only fulfilled two computational thinking indicators, as they were unable to fulfill the decomposition, generalisation, and algorithm indicators in all given problems.

Based on the analysis conducted, it can be concluded that 4 out of 6 students in a private junior high school have mastered the first to fourth indicators of computational thinking, namely decomposition, pattern

recognition, Abstraction, and algorithms. The indicator least mastered by students is the fifth indicator, generalisation, which involves concluding. These findings also highlight the role of computational thinking in problem-solving. This information can help teachers design learning processes that focus on problem-solving exercises for students. Furthermore, future researchers are encouraged to conduct studies with a larger and more diverse sample across different grade levels or school types, including public and rural schools, to compare how students with varied backgrounds demonstrate computational thinking in mathematical problem-solving. Additionally, future research could employ experimental or classroom-based interventions to examine the effectiveness of specific learning models, such as problem-based learning or STEM-integrated instruction, in enhancing computational thinking skills among junior high school students.

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