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Research Article

Charting a course: Exploring computational thinking skills in statistics content among junior high school students

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Computational Thinking (CT) skills are increasingly recognized as essential for junior high school students, especially in addressing the demands of the digital era. This study explores how CT skills—decomposition, pattern recognition, abstraction, and algorithmic thinking—manifest in learning statistics based on students' cognitive abilities. A qualitative research method was employed, involving 30 junior high school students, with six participants representing high, medium, and low initial abilities. This study uniquely maps students' CT performance in solving statistical problems, a domain that has been underexplored in relation to these skills. The results reveal significant differences based on cognitive ability: (a) students with high cognitive abilities demonstrate mastery of CT skills across all four indicators when solving statistical problems; (b) students with moderate abilities show partial competence, excelling in decomposition and abstraction but struggling with pattern recognition and algorithmic thinking; (c) students with low abilities achieve limited success, excelling in decomposition but facing challenges with the other CT skills. The novelty of this research lies in its focused examination of the intersection between CT skills and statistical problem-solving in junior high students, offering valuable insights for curriculum development. The findings suggest that integrating CT skills into statistics education enhances problem-solving capabilities across varying cognitive levels, promoting more inclusive and effective learning in the digital era.

Keywords: Cognitive abilities; Computational thinking; Junior high school; Problem-solving; Statistics education; Qualitative research

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1. Introduction

In a world increasingly shaped by computing, Computational Thinking (CT) has become an essential skill for everyone (Chakraborty, 2024; Møller & Kaup, 2023). According to Maharani et al. (2021), CT is crucial for addressing the challenges of the digital era. As a result, education systems must adapt to equip students with the cognitive tools necessary for solving problems

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computationally. This includes understanding how computers work and identifying problems that can be tackled through computational methods (Sarmasági et al., 2024). Furthermore, these skills necessitate the effective use of digital tools to solve problems within mathematical contexts (Sezer & Namukasa, 2023; Ye et al., 2023).

The integration of CT into education is crucial in the digital era, as it enhances students' problem-solving skills. Classroom observations in Grade 8 during this study revealed that high-performing students were able to effectively apply CT concepts, such as patterns and algorithms, while low-performing students struggled with abstract concepts, particularly when concrete examples were not provided. Real-life scenarios proved essential in bridging this gap, highlighting the need for adaptive teaching strategies to optimize CT integration in statistics education. Computational Thinking (CT) combines mathematical, logical, and technological abilities to shape individuals who are confident, open-minded, and adaptive to change (Kang et al., 2023; Miswanto, 2024). In education, integrating CT into mathematics and science curricula, as promoted by the Next Generation Science Standards (NGSS), has shown broad applications in areas such as algebra, geometry, probability, and statistics (Namukasa et al., 2023). Specifically, in statistics, CT offers unique opportunities to develop skills such as designing algorithms, recognizing patterns, and abstracting essential information to solve data-driven problems (Sezer & Namukasa, 2023).

While the benefits of CT are well-documented, previous studies reveal disparities in CT abilities among students. These differences are often linked to variations in cognitive abilities (Aranyi et al., 2024; Zhang & Wong, 2023). Students with high cognitive abilities consistently excel across all CT indicators, whereas those with moderate or low abilities tend to struggle, particularly in pattern recognition and algorithmic thinking (Zhang & Wong, 2023). This underscores the urgent need for targeted teaching strategies that address the diversity of students' cognitive capacities. This study aims to map the CT abilities of junior high school students, with a specific focus on statistical content. It highlights four key CT indicators: decomposition, pattern recognition, abstraction, and algorithmic thinking. By understanding the relationship between these indicators and students' cognitive abilities, educators can develop inclusive and effective teaching strategies to integrate CT into the mathematics curriculum.

Additionally, this research explores the broader educational implications of CT. The literature shows that CT not only enhances mathematical proficiency but also fosters creativity and innovation, which are vital in 21st-century education (Israel-Fishelson et al., 2020). Integrating CT into the junior high school curriculum can provide a strong foundation for critical thinking and problem-solving, particularly in statistics, where abstraction and algorithmic thinking play crucial roles (Liu, 2024).

To explore the role of CT in statistics education, this study poses the following research questions:

RQ 1) How do students with different cognitive abilities apply decomposition skills to solve statistical problems?

RQ 2) What are the differences in pattern recognition among students with high, moderate, and low abilities?

RQ 3) To what extent can students with low abilities apply abstraction compared to those with higher abilities?

RQ 4) What is the relationship between cognitive abilities and the application of CT skills in statistical problems?

RQ 5) How do students with low abilities explain their problem-solving processes, and what challenges do they face in applying CT skills?

This study aims to address a critical gap by providing new insights into the role of CT in statistics education. These insights are expected to inform the development of strategies that address diverse learning needs and promote inclusive curriculum design.

2. Literature Review

2.1. Computational Thinking

CT was first conceptualized by Seymour Papert and later popularized by Jeannette Wing in 2006, who defined it as a thought process that supports solving problems through computational steps or algorithms (Wing, 2011). Wing's framework emphasizes that CT is not limited to computer science but extends to various disciplines by teaching problem decomposition, abstraction, pattern recognition, and algorithmic thinking (Angeli et al., 2020). These elements enable learners to solve complex problems systematically while fostering critical and creative thinking.

Research highlights CT's integration across disciplines as a transformative tool for improving logical reasoning and decision-making. For instance, Sung and Black (2020) demonstrate that CT practices sharpen students' mathematical problem-solving skills, while Richardo (2020) highlight its role in enhancing computational approaches in real-world contexts. Despite these benefits, challenges such as insufficient teacher training and resources remain significant barriers (Nordby et al., 2022). Understanding the foundational concepts of CT and its applicability across disciplines underscores the importance of integrating these principles into statistics education. This integration will support the development of systematic problem-solving skills in junior high school students.

CT goes through two essential steps: the thinking process followed by decision-making or problem-solving. CT was developed by the Computer Science Teachers Association [CSTA] and the International Society for Technology in Education [ISTE], stating the characteristics of CT as follows: (a) Arranging or formulating problems, (b) analyzing problems to make them simple, (c) describing models and simulations, (d) develop solution steps, (e) determine possible solutions by identifying and analyzing and applying the process, (f) generalize the solution to other problems. Another opinion says that CT consists of several parts: problem decomposition, pattern recognition, algorithmic thinking, and generalization and abstraction (Özüdoğru, 2024). CT's ability in mathematics is the ability to think and formulate problems in computational form (Wing, 2011), which means that CT focuses on solving problems using thinking algorithms. In this research, CTs are a mindset activity that helps understand problems with appropriate images through a reasoning process to develop automatic solutions (Persky et al., 2019). The four main ideas from CT used as indicators in this research are decomposition, pattern recognition, abstraction, and algorithms. The four indicators and descriptions are explained in Table 1.

Table 1
Indicators of CT Ability

Indicators	*Description*
Decomposition	Breaking a complex problem or process into smaller, more manageable parts (sub-problems)
Pattern recognition	Identify similarities or common elements between two or more items.
Abstraction	Identify the essential and relevant parts needed to solve a problem. Hiding details so lower levels can be treated as black boxes or discarded. Generalizing a pattern
Algorithmic thinking	Instructions or step-by-step for expressing a process or solving a problem.

Note. Adapted from Huang et al (2021) and Yasin & Nusantara (2023b).

2.2. CT Skills and Constructivism Theory

CT skills and constructivism theory are deeply interconnected, focusing on developing critical thinking and active problem-solving abilities. As technological advancements drive educational priorities, these skills have become indispensable for preparing students for 21st-century challenges. Incorporating CT into curricula through robotics, STEAM (Science, Technology, Engineering, Arts, Mathematics) education, and hands-on activities helps students develop logical reasoning and problem-solving abilities essential for the modern era (Zakaria & Iksan, 2020).

Research underscores the importance of exposing students to CT at an early age. Studies show that introducing CT even at the preschool level lays a solid foundation for skill development. Papadakis et al. (2016) identify four key CT techniques—abstraction, algorithmic thinking, decomposition, and pattern recognition—as cornerstones for solving complex problems effectively. These techniques help students identify relevant information, create structured steps for solutions, break problems into manageable parts, and recognize patterns to derive solutions.

Constructivism theory, which emphasizes knowledge construction through exploration and reflection, aligns naturally with CT principles. Valls Pou et al. (2022) argue that constructivist learning fosters deeper engagement when students actively participate in problem-solving activities. CT supports this approach by offering students opportunities to apply theoretical concepts in real-world scenarios, thus building critical and logical reasoning skills (Wess et al., 2021a).

The alignment between CT and constructivism highlights their combined potential to create meaningful, student-centered learning experiences. This study will leverage this synergy to explore how junior high school students develop CT skills through active engagement with statistics education.

2.3. The Importance of Computational Thinking Skills for Junior High School Students

Computational Thinking, which involves breaking down complex problems, identifying patterns, and developing algorithmic solutions, is increasingly recognized as an essential skill for students in the digital age (Sunendar et al., 2020). This is particularly evident in mathematical statistics, where CT supports students in understanding complex data analysis and solving intricate problems (Angevine et al., 2017). The rapid advancement of technology has transformed the learning landscape, requiring students to adopt innovative ways of thinking and problem-solving (Li et al., 2020). CT encourages students to approach problems systematically, breaking them into manageable components, identifying patterns, and establishing relationships that lead to practical solutions.

At the junior high school level, integrating CT into the mathematical statistics curriculum can provide significant educational benefits. First, it enhances students' ability to understand the structural foundation of statistical problems, fostering a logical and systematic mindset (Setiawan, 2020). By decomposing complex problems into smaller parts, students can recognize patterns, relationships, and trends within data, improving their capacity to develop effective algorithmic solutions. Additionally, CT integration promotes critical thinking and problem-solving skills (Horton & Hardin, 2021). Through algorithmic design and iterative implementation, students gain the ability to analyze problems from multiple perspectives, evaluate the efficiency of their solutions, and refine their approaches for better outcomes.

Beyond immediate academic advantages, incorporating CT into junior high school mathematical statistics curricula has broader implications for students' future academic and professional development (Horton & Hardin, 2021). As the global workforce continues to evolve with technological advancements, the ability to think computationally will become a critical asset. CT equips students to apply structured problem-solving methodologies to diverse challenges, enhancing their adaptability in education and future careers.

Integrating CT skills into the mathematical statistics curriculum for junior high school students is a transformative step toward equipping them for the complexities of the digital era. By fostering logical reasoning, critical thinking, and adaptability, CT provides students with the tools needed to excel academically and professionally in a technology-driven world.

2.4. The Importance of CT Skills for Junior High School Students

Statistics is a fundamental subject taught in junior high school, designed to build critical competencies in students. These competencies include analyzing data based on distributions, averages, medians, and modes to draw conclusions, make decisions, and generate predictions, and presenting and solving problems related to these statistical measures (Schreiter et al., 2024). These skills align closely with the demands of the 21st century, where individuals are constantly surrounded by data from various sources such as social media, news outlets, and technological platforms (Maharani et al., 2021).

Understanding statistics enables students to distinguish between relevant and irrelevant information, enhancing their ability to make rational, data-informed decisions. This foundational skill is particularly important in today's data-centric world, where analyzing trends and interpreting results are crucial for problem-solving and decision-making. Through statistics education, students learn to process data systematically, recognizing patterns, drawing valid conclusions, and applying their insights to real-world scenarios.

Moreover, integrating CT skills into the learning of statistics further amplifies these benefits. By employing computational methods such as decomposition, pattern recognition, and algorithmic thinking, students can tackle statistical problems more efficiently. These skills not only enhance their statistical literacy but also prepare them for higher-level mathematical challenges and interdisciplinary applications. The integration of CT skills into the statistical curriculum equips junior high school students with essential tools for navigating the complexities of a data-driven world. By fostering analytical thinking and data literacy, these combined skills empower students to make informed decisions and succeed in both academic and real-world contexts.

2.5. Different Cognitive Levels in CT Abilities

Recent studies have demonstrated that students with varying cognitive profiles exhibit different levels of proficiency in computational thinking (Wing, 2006). Students with strong logical and analytical skills often excel in algorithmic thinking, particularly in designing efficient, step-by-step solutions to problems. On the other hand, students with creative and imaginative cognitive styles tend to excel in conceptualizing and framing problems, often identifying unconventional and innovative approaches to complex challenges (Annamalai et al., 2022). These differences highlight the diverse ways students engage with CT and the need for teaching strategies that accommodate a range of cognitive strengths.

Moreover, CT development benefits from a multidimensional and inclusive approach that leverages students' unique cognitive abilities. Recognizing these strengths allows educators to tailor instructional methods that enhance both logical problem-solving and creative exploration. Additionally, research emphasizes the importance of fostering CT skills across all educational levels—from primary to tertiary—to adequately prepare students for the challenges of the digital age (Zakaria & Iksan, 2020).

Integrating CT into the curriculum equips students with the tools necessary to navigate an increasingly complex, technology-driven world. By cultivating skills in decomposition, pattern recognition, abstraction, and algorithmic thinking, educators can empower students to become both critical problem-solvers and innovative thinkers (Cheng et al., 2023; Yeni et al., 2024). These findings underscore the critical role of adaptable teaching strategies in developing CT skills, ensuring all students can thrive in a rapidly evolving technological landscape.

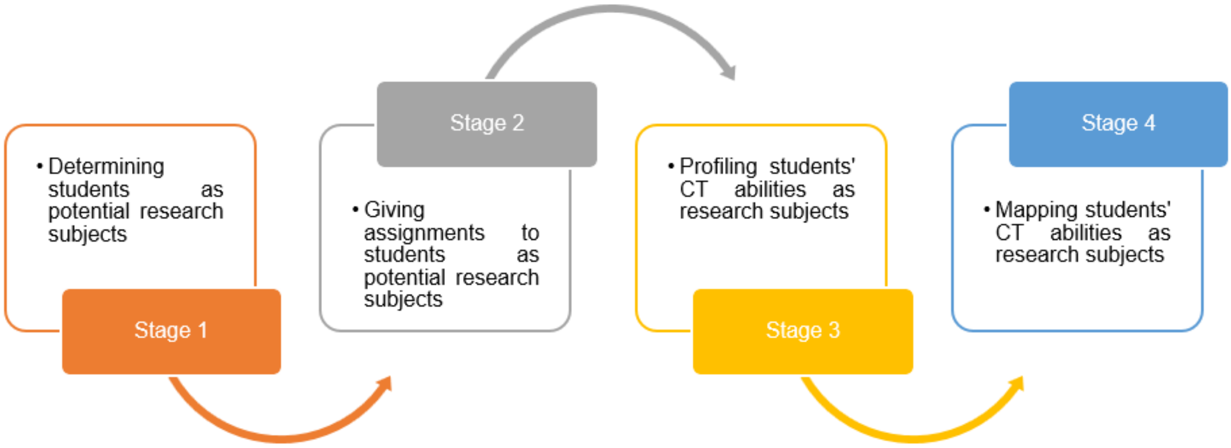
3. Materials and Methods

The research method employed in this study is descriptive qualitative (Kuckartz & Radiker, 2023). This approach was used to collect data from students' responses to descriptive questions designed to assess the computational thinking abilities of class VIII junior high school students. The questions, specifically tailored to statistics content, were developed to encourage solutions that align with key CT indicators such as decomposition, pattern recognition, abstraction, and algorithmic thinking. Through this method, the study offers a comprehensive overview of students' CT abilities and their application in statistical problem-solving.

3.1. Research Stages

This descriptive research was conducted through a systematic process comprising four stages. First, students were identified and selected as potential research participants. Second, essay assignments were distributed to these students to confirm their participation. Third, the essays produced by the participants were analyzed to profile their critical thinking abilities. Fourth, the essays were further evaluated using predefined CT indicators to map and categorize their computational thinking abilities. The detailed research workflow is illustrated in Figure 1.

Figure 1
Research stages



3.2. Research Participants

The research participants consisted of six junior high school students from Class VIII, selected from a total of 30 students. The group included four girls and two boys, representing a range of initial abilities: two students with high abilities, two with medium abilities, and two with low abilities. All participants had prior exposure to statistical content, ensuring a baseline familiarity with the subject matter relevant to the study.

3.3. Data Collection

The instrument used in this study consisted of descriptive questions based on CT indicators, specifically focused on statistical material. The questions were divided into three types: (a) Type 1 questions assessing students' ability to solve problems related to averages, (b) Type 2 questions evaluating students' ability to find data when some information is known, and (c) Type 3 questions testing students' ability to find a value when the average value and data range are known. The essay questions were adopted from the student handbook issued by the Ministry of Education, Culture, Research and Technology of the Republic of Indonesia and the Junior High School Mathematics Olympiad Question Collection. Mathematics education experts validated these questions. Before the questions were used in the study, they were first piloted with 30 junior high school students who had studied statistics. The trial results confirmed the validity and reliability of the essay questions. Students were given 80 minutes to complete the descriptive questions, which were used to assess their computational thinking abilities in statistical contexts.In addition to the essay questions, semi-structured in-depth interviews were conducted to obtain more valid data. These interviews aimed to gain insights into the student’s problem-solving processes and how they navigated CT challenges. Notably, classroom experiences were directly integrated into the data collection process. During the essay task, the researcher observed how students applied prior knowledge and problem-solving strategies learned in class. After completing the questions, students participated in follow-up interviews conducted in the classroom. This allowed the researcher to observe real-time interactions and the challenges students faced during problem-solving activities.

For example, a student commented, “I started by writing all the important data I understood from the question, and then I remembered how our teacher explained similar problems.” This illustrates the influence of classroom instruction on students’ critical thinking abilities. The recorded interviews not only documented individual responses but also captured group dynamics during discussions, offering deeper insights into the students' learning processes and problem-solving strategies.

3.4. Data Analysis

The collected data was analyzed using directed content analysis to show students’ CT abilities in mathematics and technology for grades 7-12 (Kuckartz & Radiker, 2023). Content analysis systematically interprets and describes textual data (Assarroudi et al., 2018). The analysis stages are carried out in nine steps, namely as follows:

The first step is to analyze CT capabilities, which are explained based on CT indicators (see Table 2). It is done deductively using a theoretical framework related to the studied CT topic. The second and third steps define and formulate CT indicators, which are the focus of the research. The fourth step was selecting a small sample from the collected data. The small sample chosen was two students in class VIII at a junior high school who had high initial abilities, two with medium abilities, and two with low initial abilities. This research’s total sample was six out of 30 students. This sampling was based on the initial test results and recommendations from the mathematics teacher in that class. Then, the fifth step determines how to create essay questions so that the answers lead students to think computationally. The sixth step is to analyze the primary data using documents from students’ answers to essay questions. The seventh step uses an inductive approach, grouping students’ answers with high and low initial abilities. It will be related to the pattern of students answering questions according to the CT indicators. The eighth step is to compare students’ answer patterns to determine students’ abilities in solving problems using CT indicators. Finally, the ninth step includes organizing and reporting the research.

Table 2
Aspects, Indicators, and Research Instrument Questions

Aspect	*Indicator*	*High ability questions*	*Medium ability questions*	*Low ability questions*
Decomposition (Egidi, 2015; Resnick & Kazemi, 2019)	Able to solve problem complex into smaller, well-defined sub-problems effectively.	How does breaking down a problem into smaller steps make it more manageable?	Try to explain how solving a problem can be broken down into several small parts.	Can you explain what needs to be done to finish the problem.
	Able to identify the main components of a problem	What are the main components of the problem?	Mention several parts essential to the problem .	Can you mention things to do under consideration for finishing the problem?
	Able to determine the sequence of steps needed to solve a problem.	In what order will you complete the steps to solve the problem [name problem]?	Try to sequence the steps necessary to solve the problem [name the problem].	Can you explain the sequence of steps that need to be taken to solve the problem [name the problem]?

Table 2 continued

Aspect	*Indicator*	*High ability questions*	*Medium ability questions*	*Low ability questions*
Abstraction (Knoblock, 2017; White et al., 2012)	Features significant problems and ignores details that are not relevant.	What features are essential from the problem [related problem] that need to be solved and considered to finish it?	Try to mention several essential matters from problem [mention problem] that must be solved to finish.	Can you explain what is most important to be noticed in the finish problem [mention problem]?
	Able to represent information in a more straightforward and easier-to-understand form.	How would you simplify the [name the problem] problem to make it easier to understand?	Try to explain how it would make the [name the problem] problem more straightforward to understand.	Can you explain in simpler terms what you want to achieve to solve the problem [name the problem]?
	Able to focus on aspects essential to problems and ignore details that are not relevant.	What is needed to be ignored in the problem [mention] problem] to focus on solving it?	Try to explain what does not need to be noticed in problem [mention] problem] to focus on the solution.	Can you mention things that are not important for the finish problem [mention] problem]?
Algorithm (Bacelo & Gómez-Chacón, 2023; Liu et al., 2024)	Able to develop well-defined and sequential steps to solve a problem.	How would you develop clear and structured steps to solve the problem [name the problem]?	Able to develop well-defined and sequential steps to solve a problem.	How would you develop clear and structured steps to solve the problem [name the problem]?
	Able to use clear and structured instructions to solve a problem.	How would you write clear, easy-to-understand instructions to solve the problem [name the problem]?	Try to write down the instructions you think are necessary to solve the problem [name the problem] in a way that is easy to understand.	Can you explain simply how to solve the problem [name the problem]?
	Able to evaluate and refine the steps in an algorithm.	Will you assess and improve the steps in your solution to the problem [name problem]?	Try to evaluate and improve the steps you used to solve the problem [name the problem].	Can you explain what needs to change in the way you solve problems [name the problem]
Pattern recognition (Boysen, 2019; Gillott et al., 2020)	Able to identify patterns in data or information.	Can you find the pattern in data [mention data]?	Try to explain if you find the pattern in data [mention data].	Able to identify patterns in data or information.
	Able to explain observed patterns in data or information.	How would you explain the pattern you found in data [mention data]?	Try to explain the pattern you found in data [mention data] in your way.	Can you explain? What did you find in data [mention data]?
	Able to use observed patterns to make predictions or make decisions.	What can you predict based on the pattern you found in the data [mention data]?	Able to use observed patterns to make predictions or make decisions.	What can you predict based on the pattern you found in the data [mention data]?

4. Results

The results of the research and discussion will highlight students' abilities in decomposition, pattern recognition, abstraction, and algorithmic thinking. The findings are presented by analyzing students' answers to the three types of questions, classified according to their abilities. Figure 2 presents the responses from students with high abilities in solving Type 1 questions.

Figure 2
Response of students with high ability on type 1 questions

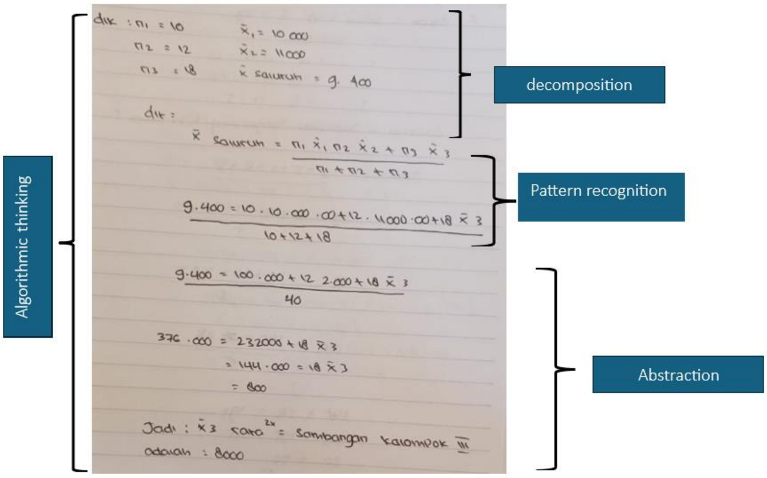


Figure 2 shows that students begin by writing down all the information they know and then identifying what needs to be resolved from the problem, demonstrating the decomposition process. They also outline strategies and steps for solving the problem, such as writing down the average formula, which reflects their ability to abstract relevant information. Next, students use the average formula to solve the problem, recognizing patterns in the process. By applying the formula, students can analyze the problem and follow the steps outlined in the formula to determine the required average, thus engaging in algorithmic thinking. This process contrasts with the responses of students with medium abilities in answering Type 1 questions, as shown in Figure 3.

Figure 3
Response of students with medium ability on type 1 questions

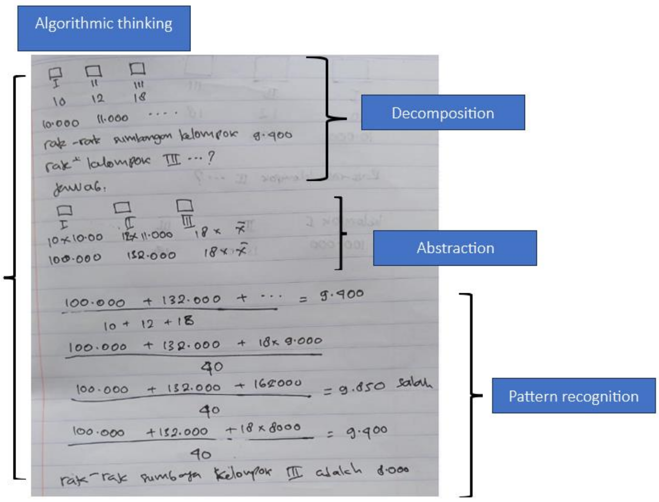


Figure 3 shows that students answered the questions by creating illustrations or diagrams to represent the information for each group, which reflects the decomposition process. Next, students used the information from each group to determine the unknown contributions from Group 3, demonstrating the abstraction process. Following this, students applied the average formula to calculate the contribution results. Initially, the student tried an average contribution of 9,000 but arrived at an incorrect class average. Then, the student attempted using 8,000 as the average contribution for Group 3, which produced the correct overall class average. This activity demonstrates the pattern recognition process.

Moreover, all the students' activities in answering type one questions are algorithmic, namely finding logical and structured solutions. Different things were found in students with low abilities in answering type 1 questions. The answers of students with low abilities can be seen in Figure 4.

Figure 4
Response of students with low abilities on type 1 questions

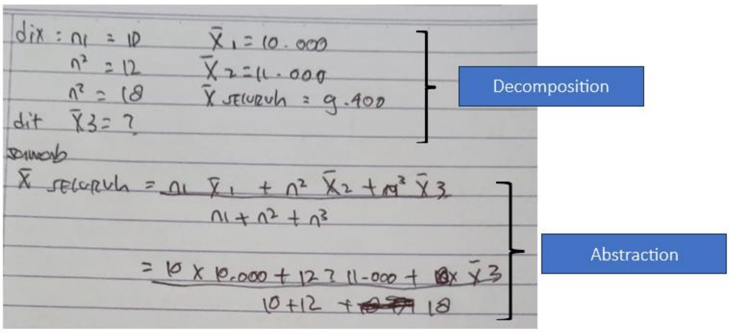


Figure 4 shows that students start writing answers by writing down important things, namely, information known from the question and information about what is being asked, which is a decomposition activity. Then, students write the average formula as a first step in solving the problem. Based on the average formula written by the students, they can apply this formula by writing down the number of the number of each group and the number of the average contribution of each group. It shows that students have carried out the abstraction process. The student's answer stops at this point. The following student cannot continue the algebraic results of the numbers he has written. The following are the results of answers from students with high ability in solving type 2 questions (see Figure 5).

Figure 5
Response of students with high initial abilities on type 2 questions

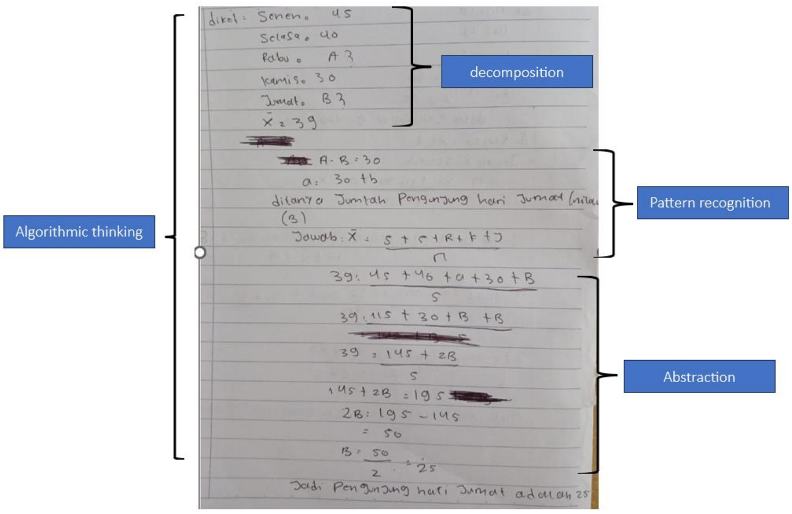


Figure 5 shows that students also use the same steps as answering type 1 questions; they start their answer by writing down essential information related to the question, which becomes a small and informative part. This activity is a decomposition process. Next, students create a mathematical equation from the information obtained, an abstraction activity. Then, students can write down the formula for the average number of visits each day using the formula. This activity is pattern recognition. Looking at the answers that students have made, it can be seen that they can think sequentially and gradually to find logical and structured solutions. This activity is an algorithmic thinking activity. The answers of students with moderate abilities on type 2 questions can be seen in Figure 6.

Figure 6
Results of students' with moderate ability on type 2 questions

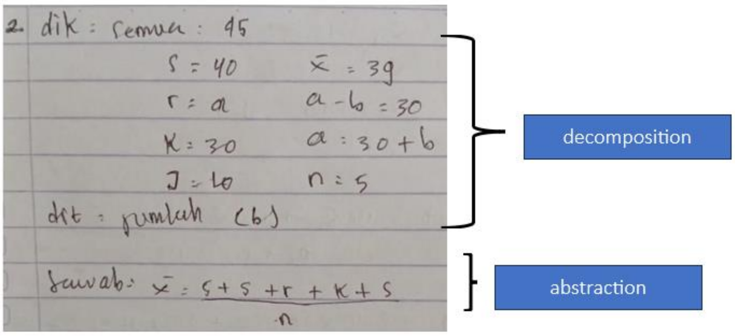
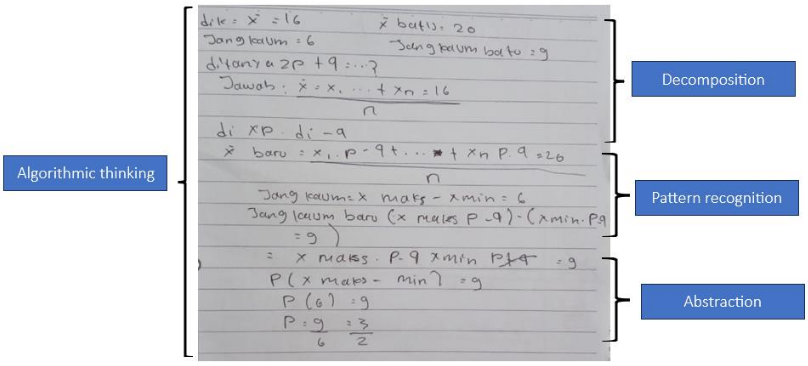


Figure 6 shows that moderate-ability students can write important information from the questions. This activity is an activity in the decomposition process. Then, students can create an equation for the answer, and this activity is an abstraction process. It can be concluded that students can only write formulas from the average, so it can be said that students cannot carry out strategies for solving these formulas. Moreover, students with low abilities cannot answer type 2 questions because they think the questions are too complex. Then, the results of the answers of students with high ability to solve type 3 questions are shown in Figure 7.

Figure 7
Response of students with high abilities on type 3 questions

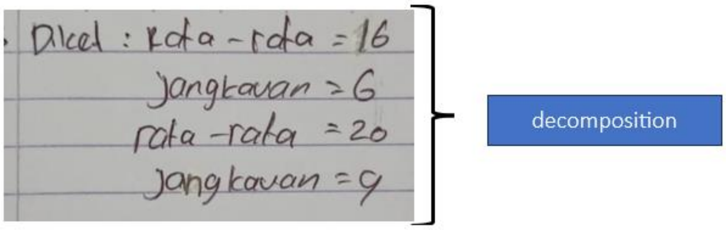


Based on Figure 7, it can be seen that students start answering questions by writing down important information, namely writing down something they know and being asked; this activity is called the decomposition process. Next, students continue their answers by writing down several equations needed to determine the steps and solutions, then continue by substituting the information obtained in these equations; this activity is called the abstraction process. By looking at Equation 1 and Equation 2 in the answer, students can find the p-value. However, from the student's answer, it can be seen that the student could not continue the strategy based on the formula that had been determined. The student could not find the value of q, so the student could not answer question type 3 successfully.

The findings differ from those of students with moderate initial ability; students with this ability failed to answer question type 3. Students with medium ability could only write down important information from a question, and this activity is a decomposition process (Figure 8).

Students with low ability did not write answers to question type 3. Students with low ability could not answer type 3 questions because the students thought the questions were too complicated.

Figure 8
Response of students with medium ability on type 3 questions



Based on the findings and descriptions of students' answers, the research results were classified based on four CT indicators: decomposition, pattern recognition, abstraction, and algorithmic thinking—these indicators map CT abilities in statistics content for class VIII SMP students. CT capability mapping is described in Table 3.

Table 3
Findings research junior high school students' high, medium, and low CT ability on statistics

CT Indicators	*Student with High Ability*	*Student with Medium Ability*	*Student with Low Ability*
Decomposition	Accessible break problem complex become smaller parts; able to identify sub-problems; can see the connection between part.	They can break down the problem into smaller parts but may experience difficulty in identifying all sub-problems or connections between parts.	Experience difficulty breaking problems into smaller parts; tend to finish the problem in a way overall without further analysis.
Abstraction	Easy to identify patterns generally; can make a mental representation of draft abstract; can generalize from specific examples.	I can identify patterns generally with help, but I have difficulty making accurate generalizations.	I experience difficulty identifying general patterns and making generalizations.
Algorithm	Can design clear and structured steps for finish problems; able to evaluate efficiency algorithm.	Can follow given algorithms but may have difficulty designing own algorithms.	Experience difficulty understanding and following algorithms; tend to use trial and error.
Pattern Recognition	Easy to identify patterns in data; can use patterns to make predictions; can classify data based on patterns.	It can identify a simple pattern, but it is possible to have difficulty identifying more complex patterns.	Has difficulty identifying patterns; tends not to use patterns to solve problems

The following describes the results of interviews with respondents regarding CT capabilities classified based on CT indicators.

4.1. Decomposition

The research results show that students consider CT decomposition related to writing down information from a given problem. Students can use decomposition to understand problems by writing down information that is considered essential. Students also often practice this activity when solving story problems. This activity helps students solve the questions given. By applying decomposition, students are more directed and focused on solving problems. Decomposition activities can improve students' ability to understand the instructions from the questions.

Previously complicated or complex instructions can be broken down into simpler ones that are easier to understand and more informative.

Practicing CT decomposition through mathematics learning can positively affect student performance. However, there are also challenges in applying decomposition in mathematics learning. Some students had difficulty decomposing activities to solve problems. Decomposition is more accessible for students with high and medium initial abilities to apply. Students with high and medium initial abilities can apply decomposition activities to solve problems. Students with low abilities have difficulty implementing decomposition activities, but this is only a portion of students; not all students with low abilities experience difficulties.

Students with low initial abilities think that decomposition is considered complicated. It depends on the student's situation when working on the questions. Some students are not used to solving problems and feel frustrated when reading questions. As one student expressed, students felt frustrated reading the questions, so they had no intention of solving them. He asserted that "I was frustrated when reading the questions; the sentences in the questions confused me." Classroom practices played a significant role in shaping students' decomposition skills. High-ability students often mirrored techniques demonstrated by their teacher in prior lessons. One student noted, "Our teacher asked us to break down problems into smaller steps, which helped me figure out the solution in today's question." This highlights the importance of teacher modeling in developing decomposition skills.

However, students with low and moderate abilities struggled to apply this technique independently. Many of them admitted to lacking confidence and familiarity with the process. Classroom group discussions became a critical support mechanism for moderate-ability students, enabling them to collaboratively identify and solve sub-problems. During a class activity, a moderate-ability student initially found it difficult to decompose a problem but succeeded after a classmate demonstrated the process. The student remarked, "When my classmate showed me how to separate the steps, I realized I had missed an important detail." This highlights the value of collaborative learning in developing decomposition skills, particularly for moderate-ability students.

Low-ability students often exhibited limited problem decomposition, focusing only on recognizing and noting surface-level facts without engaging in deeper analysis or strategy development (Knisely et al., 2020). In contrast, moderate-ability students showed a more developed capacity to decompose problems, applying this skill consistently across multiple tasks. While they might still encounter challenges with advanced problem-solving, their ability to break down complex questions into manageable steps suggests higher cognitive functioning compared to their low-ability peers.

This disparity underscores gaps in computational thinking skills, especially in methodical problem decomposition. Bridging this gap through targeted instructional strategies, such as teacher-led modeling and structured peer collaboration, could significantly enhance students' ability to approach complex problems systematically (Wu et al., 2024).

4.2. Pattern Recognition

Pattern recognition is the key to determining the right solution to a problem and knowing how to solve a specific type of problem. Recognizing common patterns or characteristics can help solve problems and help determine solutions. The research results show that students' pattern recognition cannot be seen from students' answers. Pattern recognition occurs when information from the environment is received and entered into short-term memory, causing the automatic activation of specific content in long-term memory. Pattern recognition allows students to predict and expect what will happen. The pattern recognition process involves matching the information received with information already stored in the brain. Making connections between memory and perceived information is a pattern recognition step called identification. Pattern recognition requires repetition of experience. The following is a quote from one of the high-ability students: "I answer questions by finding a suitable formula and solving it carefully until I reach the solution. However, for question number 3, I was unable to complete it due to time constraints."

Pattern recognition is a complex activity for students. Difficulty in recognizing patterns will impact students' success in developing solutions (Nguyen et al., 2020). In the present study, students with high initial abilities can correctly apply pattern recognition to the three questions. Students with moderate initial abilities can only apply to question number 1. Students with low initial abilities cannot apply pattern recognition to the three questions. The following is a quote from a low-ability student.

Pattern recognition emerged as a challenging skill, particularly for low-ability students. However, classroom practices incorporating repetitive pattern exercises and guided problem-solving enhanced students' capabilities. For instance, high-ability students were able to identify patterns in data sets during activities involving averages and medians. A student explained, "I noticed that the numbers always followed a similar trend, which made solving the problem easier."

Students with high initial abilities could apply pattern recognition across all three questions, indicating that they could effectively identify relationships, trends, or similarities within the data. This skill allows them to systematically break down and analyze problems, leading to more efficient problem-solving. Their ability to consistently recognize patterns across different questions demonstrates a well-developed capacity for abstract thinking and connecting different pieces of information (Baumanns et al., 2024).

On the other hand, students with moderate initial abilities could only successfully apply pattern recognition to the first question. This suggests that while they possess some ability to identify patterns, it is limited and might not extend to more complex or abstract problems. Their difficulty in recognizing patterns beyond the first question may stem from a lack of deeper cognitive strategies or insufficient practice with similar problems (Ling & Loh, 2023).

Moderate-ability students benefited from guided group discussions, where teachers prompted them to identify recurring elements in statistical data. One student remarked, "I didn't see the pattern at first, but when my friend pointed it out, it made sense." This finding underscores the importance of fostering collaborative learning to support pattern recognition.

Students with low initial abilities could not apply pattern recognition to any of the three questions, highlighting a significant struggle in identifying relevant patterns within the data. This inability reflects a more fundamental challenge in understanding the structure of problems, which limits their capacity to engage in computational thinking. These students likely require more foundational support and practice to develop their pattern recognition skills (Lecorchick et al., 2020). For instance, one of the students stated that "I could not find the answer because I did not know how to answer it, how to use the formula, and how to solve it. So, did not answer that question."

4.3. Abstraction

This study found general practices for solving problems in mathematics learning regarding CT abstraction. Abstraction is an essential skill for distinguishing between what is essential and what is less critical. The abstraction carried out by students in solving problems is in the form of highlighting essential parts of the instructions and finding general patterns for solving problems. In mathematics, abstraction is about finding patterns and cause-and-effect relationships. Abstraction is the CT skill most commonly used in mathematics learning. Abstraction is an essential first step in solving problems in general, namely identifying the most essential parts of a problem to form an overall picture of the solution. Abstraction is needed for activities to determine the right solution.

The application of abstraction by students in answering questions takes the form of determining the right idea as a solution to the problem or determining a suitable strategy for solving the problem and determining ideas or strategies for solving problems by formulas appropriate to the data held. The following is a quote from a student regarding abstraction in problem-solving: "When answering questions, I can identify key elements and determine solutions or ideas in the form of formulas used to solve the problems."

In applying abstraction, students with high initial abilities can apply it to the three problems given. The abstraction is applied using the chosen formula to solve the problem. High initial ability students can use appropriate ideas or strategies according to the data the students have. Students with moderate initial ability can only apply abstraction in questions 1 and 2, but in question number 3, students with moderate ability cannot. From a quote from a student with moderate initial ability who cannot apply abstraction because the student is confused about determining ideas/formulas, in the case of too much data obtained, the following is a quote from a student with medium initial ability: "I cannot write a formula or idea in question number 3 because question number 3 has data, and I cannot relate one data to another. I am confused about choosing a suitable formula or idea."

Low-ability students struggle to apply abstraction, which is the ability to focus on the essential elements of a problem while ignoring irrelevant details. Their difficulty in abstract thinking means they cannot generalize or simplify complex problems, limiting their ability to solve more advanced tasks (Akin & Murrell-Jones, 2018). In this case, they could only apply abstraction in the first, presumably simpler, question, where the need to generalize or simplify may have been minimal. This suggests that when the problem becomes more abstract or requires a more profound understanding, low-ability students find it challenging to engage with the necessary cognitive processes.

In contrast, abstraction is less challenging for high- and medium-ability students (Lakin & Wai, 2020). These students can more readily identify the key elements of a problem and ignore extraneous information, allowing them to engage with the problem more efficiently and formulate solutions. Their cognitive capacity enables them to see the bigger picture and generalize from specific examples, essential in solving more complex problems. One factor contributing to the varying levels of abstraction is the ability to think critically. This highlights the importance of developing students' problem-solving skills and their capacity for abstraction, which can be crucial for success in technical fields like electrical engineering. This difficulty with abstraction highlights a cognitive gap that low-ability students face, particularly in higher-level tasks that require strategic thinking and the ability to generalize beyond specific cases. In this sense, one of the students stated that "I do not understand the questions given, I am confused by the long questions, and I do not know what formula to use to answer the questions."

Abstraction activities in the classroom often involved simplifying complex statistical problems by focusing on critical elements. High-ability students excelled in identifying and applying relevant formulas. For instance, during a lesson on calculating averages, a student remarked, "I ignored the unnecessary details and focused only on the data required for the formula."

Moderate-ability students struggled with abstraction when faced with multiple data points but demonstrated improvement through teacher-led modeling. One student stated, "When the teacher showed us how to simplify the problem by grouping the data, it became much easier to understand." This highlights how instructional strategies can help mitigate the challenges of abstraction.

Abstraction is an activity that students can understand quickly if they pay more attention when the teacher provides explanations. Abstraction is an activity that students must have in solving mathematical problems. When students can apply abstraction, they can solve most of the problems.

4.4. Algorithmic Thinking

The research results show that applying algorithms can encourage students to be precise in their work and think structured. The algorithm is run by students using teacher practice in class. Algorithmic thinking is needed in solving mathematical problems. An algorithm is a way of creating instructions to solve a problem. Students face many challenges when applying algorithms. More students want shortcuts. Students tend to be careless in some of their solving or calculation steps. Because they want a shortcut, they have difficulty solving problems. Sometimes, students give solutions that do not make sense.

The application of student abstraction in solving problems can be seen from the results of students' answers, namely by looking at the structure of students' thinking. Algorithms in solving mathematical problems are seen from structural and sequence thinking in finding solutions. Students who think algorithmically state that by choosing a strategy or idea to find a solution, they start thinking about how to carry out the idea to the end. One of the quotes from students with high initial abilities as "I choose the right idea or strategy for the solution. Then, carefully think about and explain the idea to think from the data obtained, then choose a strategy or formula and follow the formula to the end."

Applying algorithmic thinking is not difficult for students with high abilities. Students with high initial abilities can think algorithms on all three questions. Algorithmic thinking is complex for students with medium and low abilities (Wess et al., 2021). Students with moderate ability can only apply thinking on question number one, while students with low ability cannot apply algorithmic thinking skills on the three questions. Students with medium and low initial abilities are seen answering questions using inconsistent shortcuts. Students are careless in implementing the chosen idea, so they cannot find a solution. A student with medium ability stated that:

> I do not know how to solve the problem. After I had written down what I knew and was asked about the question, I remembered the formula the teacher had taught. However, I do not know how to use the formula. I forget. So, I just filled in according to what I remembered. And I am not sure if the answer I wrote is correct.

In contrast, students with low ability have poor mathematical problem-solving skills because they cannot solve problems completely (Anjariyah et al., 2022). Algorithmic thinking was cultivated through structured problem-solving tasks. High-ability students consistently demonstrated the ability to construct logical, step-by-step solutions. One student explained, "I followed the steps we practiced in class, starting with the formula and checking each calculation carefully."In contrast, medium- and low-ability students exhibited fragmented algorithmic processes, often relying on trial and error. Classroom activities involving step-by-step demonstrations and iterative practices significantly improved these students' skills. A teacher's observation noted, "When students worked on problems in smaller groups, they became more confident in following the algorithm."

5. Discussion

The research findings indicate that students exhibited varying degrees of success in applying computational thinking (CT) indicators, including decomposition, pattern recognition, abstraction, and algorithmic thinking. In classroom settings, activities such as group projects and problem-based learning tasks were instrumental in enhancing these skills. For instance, during a project on environmental data analysis, students were tasked with breaking down complex datasets, which helped them practice decomposition in a real-world context. Decomposition, which involves breaking a problem into smaller, manageable sub-problems, was observed in students of all ability levels, although its effectiveness varied. High-ability students demonstrated a strong ability to identify and organize essential information, often using illustrations to clarify their thinking. Medium-ability students managed to decompose problems but occasionally struggled to connect sub-problems, while low-ability students faced significant difficulties in this process, often requiring guidance to focus on key elements. Studies suggest that group learning and practical problem-solving activities can enhance decomposition skills, especially for students who struggle (Humble & Mozelius, 2023)

Pattern recognition, another critical CT skill, was effectively applied by high-ability students, who were able to identify patterns in data and use them to formulate solutions. In a classroom exercise involving statistical trends, high-ability students quickly identified patterns in historical data, which allowed them to predict future trends accurately. However, medium- and low-ability students found this skill more challenging. High-ability students excelled in recognizing recurring patterns and translating them into actionable strategies, while lower-ability students often failed to connect relevant data points. This suggests that prior knowledge plays a vital role in pattern recognition, highlighting the need for educators to create opportunities for collaborative learning and discussions to foster this skill (Yasin & Nusantara, 2023).

Abstraction, which focuses on identifying essential elements while ignoring irrelevant details, also revealed disparities among students. High-ability students were proficient in selecting relevant data and determining suitable strategies, while medium-ability students demonstrated partial success, often struggling with complex data sets. During a lesson on mathematical modeling, students practiced abstraction by focusing on key variables and ignoring extraneous information, which helped them develop more accurate models. Low-ability students, however, faced significant difficulties, often failing to simplify or generalize problems. To address these challenges, structured practice and collaborative problem-solving activities can help students develop abstraction skills, enabling them to focus on critical aspects of problems (Güler & Çekmez, 2023; Sezer & Namukasa, 2023).

Algorithmic thinking, characterized by the ability to create logical, structured solutions, was observed primarily among high-ability students. These students consistently demonstrated sequential and methodical problem-solving approaches. In programming classes, high-ability students successfully applied algorithmic thinking by developing efficient code to solve complex problems, showcasing their ability to construct logical sequences. In contrast, medium- and low-ability students struggled to apply this skill, often resorting to trial-and-error methods or inconsistent shortcuts. This highlights the importance of encouraging structured problem-solving practices in classrooms, as well as providing opportunities for students to learn and refine algorithmic thinking through real-world applications (Bers, 2021).

In summary, while high-ability students exhibited competence across all CT indicators, medium- and low-ability students faced challenges that hindered their performance. The integration of real-world examples and hands-on activities in the classroom was shown to significantly impact students' understanding and application of CT skills. For example, students who participated in a collaborative project on data visualization reported a deeper understanding of abstraction and pattern recognition. These findings underscore the importance of differentiated teaching strategies and collaborative learning environments to support the development of CT skills among students of varying abilities. By integrating structured activities and fostering critical problem-solving discussions, educators can better address the needs of diverse learners in mathematics and statistics education.

6. Conclusion

Based on these findings, this research can conclude that students with low abilities are less capable of pattern recognition, abstraction, and algorithmic thinking, so they cannot apply CT indicators to solve problems. Meanwhile, students with high abilities can solve problems using the CT indicator stages. It is illustrated in the decomposition indicator, characterized by students' ability to collect important information in written form from what is known and asked from the questions. In the pattern recognition indicator, student activities are not visible in students' answers, but pattern recognition is in the form of students' activities to match questions with past experiences in their minds. Then, in the abstraction indicator, where students determine strategies for solving problems in the form of decisions taken in solving problems, this activity is marked by selecting relevant formulas. Finally, the algorithmic thinking indicator in statistics material is characterized by finding solutions in a logical and structured manner. Students with moderate abilities can solve one problem out of three problems given with indicators of decomposition abstraction and are less capable of pattern recognition and algorithmic thinking. Students with low initial abilities could not solve the three problems, but in questions one and three, the students could write decomposition indicators.

7. Limitations and Future Research

The results of this research are based on limited material, namely on statistics content for junior high school students, and include four CT indicators: decomposition, pattern recognition, abstraction, and algorithmic thinking. Three potential future studies that could overcome these limitations are (1) investigations of more significant numbers of participants; (2) Investigation of material content other than Statistics, for example, Numbers, Algebra, Measurement, and Geometry; (3) investigation of all CT indicators. These three studies could also be combined for a more thorough investigation of the opportunities and challenges of CT, with the idea of a mixed methods approach.

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