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Analyzing Computational Thinking Skills in 7th Grade Students: A Focus on Data Processing in Mathematics Education

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Abstract: Computational Thinking (CT) skills are essential in mathematics education, particularly in data processing topics. This study aims to analyze the CT skills of 7th-grade junior high school students based on four main components: decomposing, abstraction, pattern recognition, and algorithmic thinking. A qualitative phenomenological approach was employed, involving 14 students selected purposively based on their diverse academic performance levels. Data was collected through classroom observation, CT skill tests focusing on data processing tasks, and in-depth semi-structured interviews to explore students' problem-solving strategies and cognitive processes. The findings reveal varied CT competencies among students. For decomposing, 29% of students demonstrated high ability, effectively breaking down complex problems into manageable steps, while 36% exhibited moderate skills. In abstraction, the majority (57%) struggled to filter relevant data from irrelevant ones, highlighting this as a key area for improvement. Pattern recognition showed 36% of students in the high category, recognizing and logically explaining data trends, whereas 29% remained in the low category. Algorithmic thinking presented the strongest performance, with 43% of students categorized as high, showcasing structured and logical approaches to solving data-related problems. The study highlights the need for targeted interventions to strengthen abstraction and pattern recognition skills, crucial for comprehensive data analysis. By identifying strengths and weaknesses in CT skills, this research provides insights into designing more effective teaching strategies and developing CT-oriented curricula. The findings contribute to mathematics education by addressing 21st-century skills, equipping students with critical thinking and analytical capabilities needed in a data-driven world.

Keywords: computational thinking, mathematics, data processing, junior high school.

▪ INTRODUCTION

Computational thinking skills are essential in the digital age, penetrating fields such as education, engineering, business, and healthcare (Yokuş & Kahramanoglu, 2022). These skills involve problem-solving, system design, and understanding human behavior through computer science concepts (Morze et al., 2022). It is emphasized that computational thinking is fundamental for all individuals and must be integrated across disciplines to improve problem-solving abilities (Proctor, 2023). The European project focuses on fostering computational thinking across STEM subjects, providing didactic materials for teachers, and proposing curriculum integration to develop students' computational thinking skills (Tene-Tenempaguay et al., 2023). Overall, computational thinking is an increasingly important 21st-century skill for effectively navigating today's complex digital landscape while shaping global education policies and practices.

Computational Thinking (CT) involves four interrelated core skills - pattern recognition, abstraction, algorithmic thinking, and decomposition. Pattern recognition focuses on identifying similarities between problems to find solutions. Students are prompted to recognize important information while ignoring irrelevant data, allowing them to break problems down into simple, structured steps (Apriani et al., 2021; Surya et

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al., 2022). Tools such as the Computational Thinking Pattern chart have aided the development of these skills (Abdullah et al., 2019; Koh et al., 2010).

Furthermore, abstraction helps extract important features of a problem while also pinpointing similarities between objects or procedures. This skill permits simplifying intricate information into more comprehensible representations for example through labeled diagrams or concept maps (Curzon et al., 2016). Additionally, abstraction facilitates crafting novel concepts applicable to problem-solving (Chaabi et al., 2019).

Algorithmic thinking is a core ability in CT that permits designing logical and organized solutions through a series of rules or steps. For example, applying genetic algorithms and hybrid algorithms addresses solving mathematical issues like linear or quadratic equations (Christi & Rajiman, 2023; Hidayat et al., 2023). A deep grasp of algorithms helps address problems in a systematic manner (Zuod & Namukasa, 2023).

Lastly, decomposition plays a role in breaking down big problems into smaller, more manageable parts. These skills underlie software development, algorithm design, and complex problem-solving. Although it often faces challenges due to the high level of complexity, a structured decomposition approach is able to simplify the problem-solving process (Charitsis et al., 2023; Fried et al., 2018). Overall, these four skills are important foundations in various technical fields, including mathematics education.

Computational thinking allows for logical and analytical creative problem-solving. Pattern recognition and algorithmic thinking decompose complex issues (Proctor, 2023; Yokuş & Kahramanoglu, 2022). Such analytical skills benefit mathematics learning by promoting depth of understanding and real-world problem-solving (Demir et al., 2022). Accordingly, integrating computational thinking optimally prepares younger generations for an increasingly digital society.

While essential, implementing computational thinking in schools presents obstacles. Fundamental concepts like abstraction and parsing problems into parts challenge many students, hindering complex math problem-solving (Chongo et al., 2020). Additionally, teachers often lack training and resources, feeling less confident in classroom instruction and resulting in suboptimal skill development, especially regarding data processing in 7th grade junior high (Mukhibin & Juandi, 2023).

While mathematics instructors hope computational thinking can effectively boost how pupils solve issues and grasp complex notions like information handling, learners want learning that engages and relates to actual problems. Thus, both parties have high hopes for integrating computational thinking to strengthen math education.

The disparity between facts and aspirations is the primary difficulty in computational thinking's development for 7th grade middle schoolers. Students struggle with basics like abstraction and decomposition, whereas educators expect them to examine and analyze data skillfully. Moreover, scarce resources and conventional instruction hinder achieving these goals. This gap highlights the need for a targeted strategy to advance learners' computational thinking abilities in information processing.

Previous studies examined applying computational thinking in schooling. Abdullah et al. crafted a computational thinking-based program assisting pupils understand data patterns in data handling. Chongo et al. researched the challenges pupils face acquiring fundamental skills and how instructors anticipate learners can utilize computational thinking. Mukhibin and Juandi explored how limited assets and less groundbreaking teaching techniques obstruct realizing anticipated outcomes. Ramaila and Shilenge reviewed how learners want learning connecting mathematical ideas to real-world issues to engage and apply what they gain. Elicer and Tamborg investigated if computational thinking can successfully upgrade how students solve issues and their capacity to grasp abstract notions.

Another study by Elicer & Tamborg, (2023) shows that CT can help students improve their algorithmic thinking skills in solving data problems. In addition, research by Ramaila & Shilenge, (2023) found that CT-based activities are effective in improving students' understanding of data in the context of mathematics learning. However, there has been no research that specifically analyzes students' CT abilities in data processing using the same method as this study.

This study is unique because it focuses on analyzing the CT ability of 7th-grade junior high school students in data processing materials. In addition, the study not only measured, but also explored in depth each component of CT, namely decomposition, abstraction, pattern recognition, and algorithmic thinking. Thus, this research makes a new contribution to the CT literature in the field of mathematics education.

The urgency of this research lies in the need to improve the CT ability of junior high school students, especially in data processing, in order to support mathematics learning that is relevant to the demands of the 21st century. By understanding students' CT abilities, teachers can develop more effective learning strategies to equip students with the critical, analytical, and applicative skills necessary in real life.

This study aims to analyze the CT ability of 7th-grade junior high school students in data processing materials, especially in the aspects of decomposition, abstraction, pattern recognition, and algorithmic. Provide a detailed overview of students' strengths and weaknesses in each component of the CT to support the development of more effective mathematics learning strategies.

This research has various uses both theoretically and practically. Theoretically, this research is expected to contribute to the development of literature on Computational Thinking (CT) in the context of mathematics learning, especially data processing materials at the junior high school level. This research can also be a reference for future researchers who are interested in analyzing students' CT abilities in aspects such as decomposition, abstraction, pattern recognition, and algorithmic thinking.

Practically, the results of this study can help mathematics teachers understand students' abilities in CT, so that they can design more effective and relevant learning strategies. In addition, students are also expected to gain a more meaningful learning experience, which supports their ability to think logically, analytically, and creatively. The findings of this study can also be considered for policymakers in integrating the concept of CT into the educational curriculum.

In this study, Computational Thinking (CT) is defined as the ability to think that involves the process of solving problems through four main components. First, decomposition is the process of breaking down a large problem into smaller, well-
Practically, integrating computational thinking abilities into mathematics pedagogy could meaningfully enhance students' problem-solving skills. Students who can decompose complex issues, recognize patterns, and think algorithmically are better equipped to tackle challenging multi-step logic problems. In addition, cultivating computational perspectives supports creative and analytical thinking applicable across disciplines. These findings suggest policymakers should explore integrating CT concepts into curricula to

provide students varied learning approaches complementing conventional mathematics instruction.

Furthermore, data presentation and analysis are central to computational thinking. In this study, students' proficiency with organizing, visualizing, and interpreting numerical information to draw evidence-based conclusions was examined. Their ability to break down raw numbers into clearer tables, graphs, or diagrams demonstrated skills in abstraction and decomposition. Methodically structuring data insights further reflected pattern recognition and algorithmic stratagems. Collectively, cultivating these computational abilities may encourage more engaging, meaningful mathematics learning experiences.

Defined parts to make it easier to solve. Then, abstraction is the ability to recognize patterns, ignore irrelevant information, and focus on the important elements of a problem. Furthermore, pattern recognition is the ability to identify similarities or patterns in data, which can help find more systematic solutions. Finally, algorithmic thinking is the process of designing logical and structured steps to solve a problem effectively. The data processing material in this study includes the ability of students to organize, analyze, and present data in the form of tables, graphs, or diagrams, as well as use the data to make conclusions.

▪ METHOD

Research and Design

This research uses a qualitative approach with a phenomenological type This approach was chosen to deeply explore the experience and understanding of 7th grade junior high school students related to Computational Thinking (CT) skills in data processing materials. The phenomenological approach allows researchers to understand how students experience and express their CT abilities through interactions in mathematics learning. This research was carried out during the period from April 25, 2024, to May 16, 2024, at one of the Tsanawiyah Madrasah (MTS) in the city of Bandung.

Participants

This study involved the population of 7th-grade students in one of the junior high schools in Bandung. The research sample consisted of 14 students who were selected using the purposive sampling technique. The sample selection criteria include various levels of academic ability (high, medium, and low) based on the recommendations of mathematics teachers. In addition, other factors such as the level of digital literacy and the socio-economic background of the students are also considered to ensure a representative sample. The selection of students was carried out to describe the variation of Computational Thinking (CT) abilities in the context of data processing learning.

The research procedure involves several stages. In the preparation stage, the researcher developed research instruments, including CT ability test questions, observation guidelines, and interviews. These instruments are validated by experts before use. The observation stage was carried out during four learning sessions (90 minutes/session) to observe students' interaction with data, problem-solving strategies, and involvement in group discussions. Then the CT ability test, test is carried out to evaluate the four main components of CT, namely decomposing, abstraction, pattern recognition, and algorithmic thinking. Next: Semi-structured interviews are conducted with selected students to dig into their understanding of problem-solving strategies. The final stage of data analysis from observations, tests, and interviews were analyzed using a thematic approach to identify patterns of students' CT abilities.

Data Collection Techniques

This study uses two types of instruments, namely test instruments and non-test instruments, which are designed to evaluate the Computational Thinking (CT) ability of grade 7 students on data processing materials. Each instrument is developed based on CT indicators and has been validated to ensure its reliability. Test Instruments The test instrument is in the form of a description question designed to measure the four main components of CT: decomposing, abstraction, pattern recognition, and algorithmic thinking. The test consists of four question items, with each item designed to evaluate specific indicators as follows.

Question 1 measures the ability to decompose, which is the ability of students to break down data processing problems into small and well-defined steps. Example question: "Describe the steps that will be taken to calculate the total sales of goods for a week based on the daily data provided."

Question 2 measures abstraction ability, which is the ability of students to identify relevant data and ignore irrelevant data. Example question: "Determine a pattern from the test score data of 7th-grade students and identify the data that is important for compiling the graph."

Question 3 measures the ability to recognize patterns, namely the ability to recognize patterns in data and explain the relationships between data logically. Example question: "Based on a pie chart, describe a pattern of the percentage of students who like different types of sports in grade 7."

Question 4 measures algorithmic thinking skills, namely the ability to arrange logical and structured steps to solve problems. Example question: "Create an algorithm to calculate the average book sales in a year based on the monthly data provided".

This test instrument was developed based on guidelines from the research of Grover & Pea (2013) and Shute et al. (2017). The validity of the test is tested through trials with different groups of students, resulting in a good level of construct validity. The reliability of the test was test using internal consistency analysis with a reliability coefficient of 0.85.

Non-test instruments include observation and interview guidelines to explore more deeply the students' CT abilities. The Observation Guidelines are designed to evaluate student engagement in learning, problem-solving strategies, and interactions with processed data. There were three main indicators observed, namely involvement in group discussions, the use of relevant data, and the ability to formulate logical steps. Each indicator is represented by two to three observation items. Interview Guidelines are used to explore students' understanding of problem-solving strategies and their thought processes. The interview focused on four CT components, with each component represented by two to three questions. Example questions for algorithmic thinking: "How do you define the steps to calculate the total and average of the given data?"

This non-test instrument is developed based on relevant literature and adapted to the context of the research. The validity of non-test instruments is obtained through expert validation, while reliability is ensured by triangulation of data from observations, interviews, and tests. With this approach, the data obtained covers various aspects of students' CT in-depth and comprehensively, thus supporting a more comprehensive analysis of their CT abilities.

The data was analyzed using thematic analysis techniques. This process includes steps such as data reduction, grouping based on emerging themes, and data interpretation to identify relevant patterns and trends. This analysis is designed to answer the research objectives by demonstrating students' CT abilities in depth based on the data collected. The research adheres to ethical principles, including maintaining the confidentiality of students' identities, seeking written consent from students, and o

Research Instruments

The researcher serves as the main instrument in this research and is involved in the process of planning, implementing, collecting, analyzing, interpreting, and making research conclusions. This research has supporting instruments for the test, namely question descriptions, and non-test instruments, such as interview guidelines, and documentation. The researcher used a test in the form of a description question on the data processing material. This test is carried out to determine students' computational thinking skills. The following CT test indicators for students are in Table 1.

This scoring guideline is based on adaptations of the research of Brennan & Resnick, (2012); Grover & Pea, (2013); Selby & Woollard, (2010); and Shute et al., (2017).

Table 1. Computational thinking test indicators

No question	Sub Material	CT Components	CT Indicator	Question Indicators
1.	Data Processing	Decomposing	Break down the problem into smaller, well-defined steps.	Break down the data problem to determine the processing steps.
2.		Abstraction	Identify patterns and relationships between data.	Identify patterns and relationships between data in tables.
3.		Pattern Recognition	Identify patterns and relationships between data.	Identify patterns and relationships between data in pie charts.
4.		Algorithmic Thinking	Develop a logical and structured sequence of steps to solve the problem.	Developing an algorithm to calculate the average data in the book sales table in

Table 2. Computational thinking test score guidelines

CT Components	Score 3 (High)	Score 2 (Moderate)	Score 1 (Low)	Score 0 (None)
Decomposing	Breaking down data processing problems into logical and systematic steps.	Breaks down most of the data processing problems, but there are less obvious steps.	Breaks down a few data processing problems, but the steps are illogical or uncomplicated.	It does not break down data processing problems or irrelevant steps.
Abstraction	Identify	Identify most	Identify data in	Unable to identify

	critical data and ignore irrelevant data to simplify the problem.	of the important data, but there is less relevant information.	general, but are not able to filter out irrelevant information.	important data or irrelevant mentioned data.
Pattern Recognition	Recognize data patterns clearly and explain the relationships between data logically.	Recognizing patterns is simple, but the explanation of the relationships between data is incomplete.	Recognize patterns in general without explaining data relationships with strong logic.	Not recognizing patterns or relationships between data, or providing irrelevant logic.
Algorithmic Thinking	Arrange logical and structured steps for data processing, such as calculating totals or averages.	Drafting most of the steps is logical, but there are steps that are less clear or inappropriate.	Outline the basic steps, but they are not entirely logical or structured.	Not compiling logical steps for data processing or the steps provided are irrelevant.

Each component is graded using a scale of 0–3, with a maximum score of 12 for all The assessment of the results of students' abilities in the allocation of the other four components of Computational Thinking was used to classify them into three main categories. The high category includes students with 75% to 100% of this maximum score, i.e. with excellent categorization across all aspects assessed. Then, the intermediate category includes a score of 50% to 74%, indicating that the ability is quite good but needs reinforcement in certain aspects. Lastly, the low category is dominant at less than 50% of these scores, meaning students with significant difficulty mastering Computational Thinking skills.

▪ RESULT AND DISSCUSSION

Students' Computational Thinking (CT) skills were analyzed based on four main components, namely decomposition, abstraction, pattern recognition, and algorithmic thinking, according to data processing materials. Each component is graded using a scale of 0–3 based on pre-designed scoring guidelines. The results of the study can be seen from the distribution of student scores in each category (high, medium, low) as presented in Table 3.

Table 3. Table of results of computational thinking test

CT Components	High Category (%)	Medium Category (%)	Low Category (%)
Decomposing	29	36	36
Abstraction	21	57	21
Pattern Recognition	36	29	36
Algorithmic Thinking	43	29	29

The results of Table 3 analysis of the Computational Thinking (CT) ability of grade 7 students in the data processing material showed variations in the level of ability in four main components, namely Decomposing, Abstraction, Pattern Recognition, and Algorithmic Thinking.

In the Decomposing aspect, as many as 29% of students are in the high category, which shows their ability to break down data processing problems into logical and systematic steps. However, there are 36% of students are only in the medium category, while the other 36% are in the low category. This shows that some students still have difficulty solving problems in a structured manner.

The student's ability in the aspect of Abstraction or identification of important data shows that the majority of students, namely 57%, are in the medium category. Students who were able to effectively identify important data and ignore irrelevant information (high category) amounted to only 21%, while another 21% were in the low category. These findings indicate that there are challenges in filtering and simplifying information.

In the Pattern Recognition aspect, as many as 36% of students are in the high category, which reflects their ability to recognize data patterns clearly and explain the relationships between data logically. On the other hand, 29% of students are in the medium category, while another 36% of students are in the low category. This difference reflects the gap in students' ability to understand data patterns.

Algorithmic Thinking ability shows better results than other components. A total of 43% of students were in the high category, which indicates their ability to devise logical and structured steps to solve problems. However, there were 29% of students in the medium category and another 29% in the low category, which shows that there is still room to improve algorithmic thinking skills in students.

Before entering the in-depth analysis, Table 4 presents a reduction of data containing the total score and a description of the category of Computational Thinking (CT) ability based on the test results for each participant.

Table 4. Categories of students' computational thinking skills

Subject	Score	Description
AG	12/12	Tall
AS	8/12	Middle
AN	6/12	Low

The test results showed that the AG participant had high CT ability, AS was in the medium category, and AN was in the low category. This analysis was reinforced with interviews to provide a deeper understanding of each participant's abilities on the four components of CT such as decomposition, abstraction, pattern recognition, and algorithmic thinking.

Decomposition

Data decomposition was an area where AG demonstrated remarkable facility. During the trial, AG skillfully parsed computational issues into sensible sequences for instance, segregating daily statistics to derive weekly sums and monthly normals. This was substantiated in the dialogue where AG noted, "I initially tabulate earnings apiece day so as to then tot up for the hebdomadal sum. Ordinarily, I separate the sum by the number of days." Furthermore, AG had the ability to break down even the most intricate of issues into straightforward steps through visualizing the key facets and relations between disparate parts, granting AG a comprehensive grasp and bringing clarity to otherwise muddled subjects. On the contrary, the AS and AN are having difficulties. As said, "I tried to separate the data, but I was confused when it came to calculating the average," while AN only summed directly without breaking down the data in a structured way. These findings support the research of Selby & Woollard, (2010), which states that students with high decomposition ability are able to break down problems into systematic steps compared to students with moderate or low ability. This can be proven through the image of the AG's answer in Figure 1.

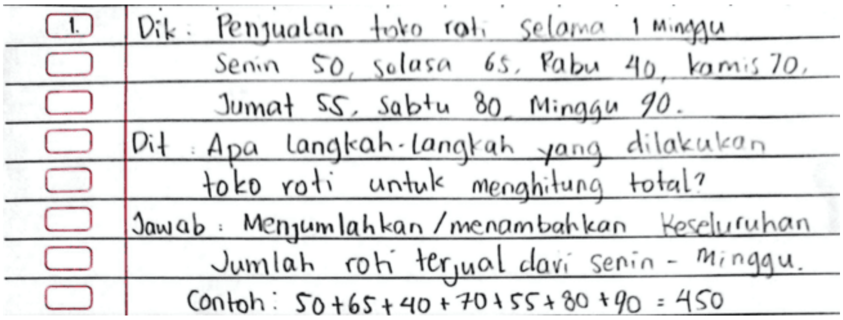
1. Dik: Penjualan toko roti selama 1 minggu
Senin 50, selasa 65, Rabu 40, kamis 70,
Jumat 55, Sabtu 80, Minggu 90.
Dit: Apa langkah-langkah yang dilakukan
toko roti untuk menghitung total?
Jawab: Menjumlahkan/menambahkan keseluruhan
Jumlah roti terjual dari senin - minggu.
Contoh: 50+65+40+70+55+80+90 = 450

Figure 1. The answer to AG decomposition

Abstraction

In the aspect of abstraction, AG again showed high ability. In the interview, he stated, "I only use relevant data, such as the number of daily sales. I ignored other data," which shows that AG is able to filter out important information and ignore irrelevant data. In contrast, the AN and the AS have difficulty in filtering data. AN said, "I was confused about which data was important." while the AS said, "I know the daily data is important, but I'm not sure if I should ignore the other data." This finding is in line with Mukhibin & Juandi, (2023), who reported that abstraction is a difficult component of CT because it requires strong information filtering capabilities. This can be proven because AN did not answer question number 2 regarding abstraction.

Pattern Recognition

In pattern recognition, AG is able to clearly recognize daily sales trends and explain the relationships between data logically. In the interview, he stated, "I saw higher sales on Monday, so that's the pattern." However, the AN found only a simple pattern without in-depth analysis, saying, "I only found that there are a few days with the same number," while the AS. Failed to discern the motif whatsoever, responding, "I was unable to isolate a motif from that evidence." These discoveries uphold the investigation of Chongo et al., (2020), which expresses that pattern identification is regularly a test for understudies in light of the fact that it expects profound investigation. This can be shown through the visual of the AS's solution in Figure 2. The understudy, indecisive in their investigation, fizzled to distinguish the example in the information gave, paying little mind to the presence of a clear design that could be seen on nearer assessment. In such a way, it affirms past exploration recognizing that finding examples crosswise over various cases of information is one of the hardest logical abilities to create in AI frameworks just as understudies new to the subject.

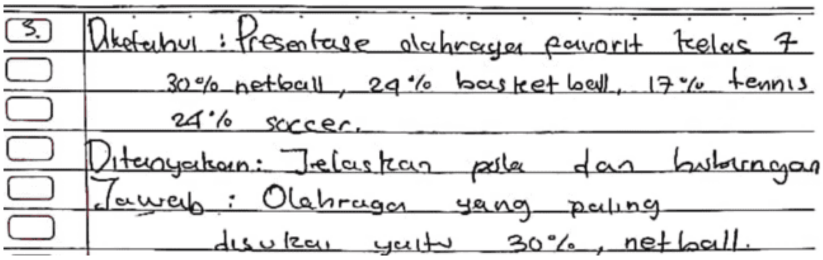
5.
Diketahui : Presentase olahraga favorit kelas 7
30% netball, 24% basket ball, 17% tennis
24% soccer.
Ditanyakan: Jelaskan pola dan hubungan
Jawab : Olahraga yang paling
disukai yaitu 30%, netball.

Figure 2. The answer to AS pattern recognition

Algorithmic

On the aspect of algorithmic thinking, AG shows clear logical steps in tests and interviews. He began, "After aggregating, I developed a straightforward formula for finding the average: total amount divided by the number of days," indicating strong logical abilities. Both the artificial neural and adaptive systems have more constrained capacities. The neural system acknowledged, "I ordered the steps correctly, but sometimes miscalculated during the process," while the adaptive system stated, "I followed the prescribed process of the task, but was perplexed if the final step was inaccurate." These conclusions support previous research (Ramallah & Shilenge, 2023), which contends that algorithmic thinking is relatively more comprehensible for students because of its organized nature and can be enhanced through methodical practice. This can be substantiated by examining the graphical representation of the adaptive system's response in Figure 3.

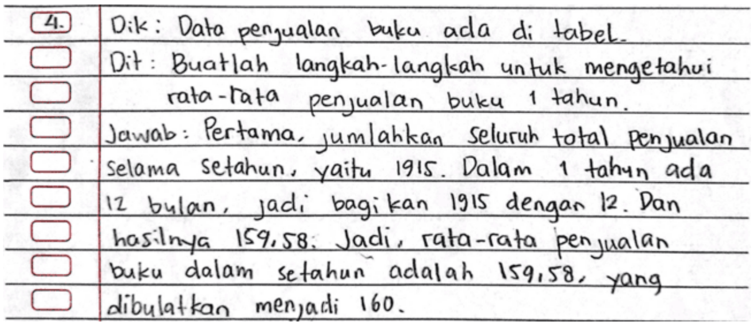
4.
Dik: Data penjualan buku ada di tabel.
Dit: Buatlah langkah-langkah untuk mengetahui
rata-rata penjualan buku 1 tahun.
Jawab: Pertama, jumlahkan seluruh total penjualan
selama setahun, yaitu 1915. Dalam 1 tahun ada
12 bulan, jadi bagikan 1915 dengan 12. Dan
hasilnya 159,58. Jadi, rata-rata penjualan
buku dalam setahun adalah 159,58, yang
dibulatkan menjadi 160.

Figure 1. The answer of AG alghorims

The results of the study showed variations in Computational Thinking (CT) abilities of 7th-grade junior high school students based on indicators of decomposition, abstraction, pattern recognition, and algorithmic thinking. Analysis of tests and interviews revealed that each subject had different abilities on each indicator. To make it easier to understand, Table 5 presents the CT indicators that were met by each subject based on the results of the analysis.

Table 5. Indicators of computational thinking fulfilled by the subject

Subject	Indicators			
	Decomposition	**Abstraction**	**Pattern Recognition**	**Algorithm**
AG	✓	✓	✓	✓
AS	✓	✓	-	✓
AN	✓	-	-	✓

The results of this study provide important insights into the Computational Thinking (CT) ability of grade 7 students on data processing materials. Based on the findings, the proportion of students in the high category in the aspects of Decomposing and Algorithmic Thinking shows the significant potential of students in solving problems and compiling logical steps. However, the aspects of Abstraction and Pattern Recognition are still the main challenges for the majority of students, as shown by the dominance of medium and low categories in these two aspects. These findings confirm the need for learning interventions that are more focused on strengthening abstraction and pattern recognition skills to improve students' critical and analytical thinking skills.

In addition to analyzing individual abilities in each CT component, this study also explores the relationships between components to identify significant correlation patterns that will be shown in Table 6.

Table 6. Correlation between components of students' computational thinking

Component CT	Decomposing	Abstraction	Pattern Recognition	Algorithmic Thinking
Decomposing	1.00	0.76	0.81	0.84
Abstraction	0.76	1.00	0.68	0.72
Pattern Recognition	0.81	0.68	1.00	0.89
Algorithmic Thinking	0.84	0.72	0.89	1.00

Decomposing and Algorithmic Thinking had a high correlation (0.84), indicating that students who were able to solve problems logically also tended to be able to structure good algorithmic steps. Pattern Recognition and Algorithmic Thinking also had a very high correlation (0.89), indicating a close relationship between the ability to recognize patterns and arrange logical steps to solve problems.

Abstraction had a moderate correlation with all other components, with the highest correlation value for Decomposing (0.76), showing a moderate relationship between the ability to filter relevant data and solve problems.

These results suggest that there is a significant relationship between the various components of CT. Good ability in one component, such as pattern recognition, tends to be related to high ability in other components, such as algorithmic thinking. However, abstraction tends to have a weaker relationship compared to other components, so it needs more attention in learning development. The correlation results showed that students' ability to decompose and algorithmic thinking had a strong relationship. These findings support the research of Ramallah & Shilenge (2023), which states that problem-solving abilities are often the basis for putting together effective algorithms. In contrast, the correlation of abstraction with other components was weaker, suggesting that this aspect needed more reinforcement in learning.

This study contributes to the CT literature by showing a strong relationship between Pattern Recognition and Algorithmic Thinking, as well as the importance of improving abstraction through a more directed learning approach. These results can be the basis for developing a more effective CT-based curriculum.

From a practical perspective, these results indicate that teachers can utilize Computational Thinking-based learning strategies, such as the use of interactive simulations or data-based case studies, to help students overcome difficulties in the aspects of abstraction and pattern recognition. In addition, these results also provide a basis for the development of a curriculum that integrates CT elements more explicitly in mathematics learning, especially data processing materials.

However, this study has some limitations that need to be considered. First, the research subjects consisted of a sample limited to a single school, so generalizing the findings to a wider population needed to be done carefully. Second, the qualitative approach used provides in-depth insight into the student's abilities, but may lack a more comprehensive quantitative picture. Third, the validity of the instruments used, although referring to previous studies, has not been further tested in a local context, which could affect the interpretation of the results.

These implications and limitations provide direction for further research, such as testing the instrument in a wider population and developing more innovative CT-based learning strategies. Further research is expected to further explore the relationship between computational thinking ability and mathematics learning outcomes, as well as explore the factors that affect the success of CT implementation in the classroom.

▪ CONCLUSION

This investigation set out to dissect the Computational Thinking (CT) aptitudes of grade 7 understudies concerning information preparing materials with an accentuation on four central parts, particularly separating, abstraction, example acknowledgment, and algorithmic thinking. The outcomes uncovered that understudies' abilities in CT tended to fluctuate broadly, with most falling somewhere in the range of average in a large portion of the territories considered. Breaking down and algorithmic thinking appeared to be more grounded regions than abstraction and example acknowledgment, which keep on testing understudies the most. Not at all like customary assessments may propose, there was no single way youths grasped these key CT ideas. A handful approached the difficulties with phenomenal deftness while others needed more invested energy honing delegation and design acknowledgment through hands on learning exercises adjusted to their diverse pacing.

In particular, students' decomposing ability showed that most students were able to break down problems into logical steps, although there were still difficulties in low-category students. In the aspect of algorithmic thinking, the majority of students are able to arrange structured steps, but some students experience obstacles in logical consistency. On the other hand, in the aspects of abstraction and pattern recognition, students tend to have difficulty in filtering important information and recognizing data patterns logically, which indicates the need to strengthen learning in both aspects.

These findings make an important contribution to understanding students' CT abilities at the junior high school level and their relevance to mathematics learning, especially data processing materials. The results of this research can be the basis for teachers to develop more innovative learning strategies, by emphasizing the reinforcement of abstraction and pattern recognition. In addition, this study also provides recommendations for the development of a curriculum that integrates the concept of CT to prepare students to face the challenges of the 21st century.

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