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Evaluating Computational Thinking and Its Influencing Factors in Vocational Mathematics Learning

Muhammad Jibran Al'fauzi*, Megita Dwi Pamungkas, & Arifta Nurjanah
Mathematics Education Study Program, Universitas Tidar University, Indonesia

*Corresponding email: muhjibranalfauzi@gmail.com

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Abstract: Computational thinking (CT) is an important competency for vocational high school students because it supports systematic problem-solving in mathematics and vocational contexts. This study aimed to describe the CT ability profile of tenth-grade students at SMK Citra Medika Kota Magelang and identify the factors influencing it. This study used a descriptive qualitative approach. The participants were 30 students of Class X Nursing 4, and six students were selected as main subjects through purposive sampling based on high, medium, and low CT ability categories. Data were collected through a CT ability test, an open-ended questionnaire, and interviews. Data validity was examined using triangulation, while data were analyzed through data reduction, data display, and conclusion drawing. The findings showed that students' CT abilities varied across decomposition, abstraction, pattern recognition, and algorithmic thinking. High-category students met all indicators; medium-category students met most indicators but still struggled with algorithmic thinking; and low-category students struggled with abstraction, pattern recognition, and algorithmic thinking. CT ability was associated with prerequisite mathematical knowledge, learning motivation, learning independence, learning environment, and learning resources.

Keywords: contextual problems, computational thinking, health context, mathematics learning, vocational high school.

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INTRODUCTION

Mathematics learning plays an important role in developing students' logical, systematic, analytical, and problem-solving abilities. These abilities are increasingly important in twenty-first-century learning because students are expected not only to understand mathematical concepts but also to use them to solve contextual problems. At the vocational high school level, mathematics has a practical function because it is related to students' readiness to face vocational tasks and workplace situations. Therefore, mathematics learning should focus on habituating students to understand problems, select information, recognize regularities, and arrange solution steps in a structured manner (Sinaga et al., 2023).

One ability closely related to structured problem solving is computational thinking (CT). CT is a thinking process used to formulate problems and design solutions systematically through concepts related to computer science, although it is not limited to computer use. Tariq et al. (2025) explain that computational thinking is a fundamental skill that involves solving problems, designing systems, and understanding human behavior through the fundamental concepts of computer science. In addition, Subramaniam et al. (2022) state that CT in mathematics education is related to students' ability to design computational solutions, think algorithmically, and develop skills such as abstract thinking, problem solving, pattern recognition, and logical reasoning.

In mathematics learning, CT can help students understand problems more clearly. Through decomposition, students can break complex problems into smaller parts. Through abstraction, students can select relevant information and ignore unnecessary information. Through pattern recognition, students can identify regularities in the data or situations presented. Furthermore, through algorithmic thinking, students can arrange solution steps sequentially, logically, and systematically. These four indicators align with Weller et al. (2022), who state that CT ability includes decomposition, abstraction, pattern recognition, and algorithmic thinking. This ability also supports students in solving mathematical problems; Weller et al. (2022) found that CT supports problem-solving processes through decomposition, abstraction, and algorithms. Integrating CT into mathematics learning should be designed through activities that conect mathematical reasoning and computational reasoning, so students not only perform calculations but can also model problems, construct procedures, and apply problem-solving strategies systematically (Musaeus & Musaeus, 2024).

CT ability is important for vocational high school students because vocational education aims to prepare students to enter specific occupational fields. In health-related vocational schools, students encounter situations that require accuracy, data processing, and systematic solution procedures. For example, students may face problems related to drug dosage calculations, medical supply management, patient data interpretation, and analysis of patient progress. These situations require the ability to select important information, recognize patterns of change, and apply appropriate calculation procedures. Thus, CT is not only relevant to mathematics learning but also closely related to students' readiness to work in health-related vocational contexts. Hermans et al. (2024) emphasize that vocational education needs to integrate CT to prepare students for modern technology-rich workplaces, including non-technical vocational fields such as healthcare that involve medical technology and data analysis.

Previous studies have shown that the development of CT in schools still faces several challenges. Mohd Rosli & Mohd Matore (2023) found that vocational students still struggled to understand the fundamentals of CT, showed low interest in programming, and had not been adequately assessed for CT literacy. Chytas et al. (2024) also emphasized the importance of CT in secondary mathematics education because CT can support mathematical concept understanding and problem-solving skills. Other studies indicate that mathematical ability and prior learning experiences can contribute to students' CT competence. Lee et al. (2023) reported that mathematics learning helps predict students' CT competence, whereas Kaup et al. (2023) emphasized that integrating CT can enhance students' mathematical understanding. Fitrah et al. (2025) showed that project-based learning combined with a flipped classroom can improve students' CT skills, particularly in decomposition, pattern recognition, and abstraction in mathematics learning.

Although CT has been widely studied in mathematics learning, studies that specifically describe the CT ability profile of health-vocational high school students remain limited. Based on preliminary observations at SMK Citra Medika Kota Magelang, the mathematics teacher implemented innovative learning approaches, such as Problem-Based Learning and contextual higher-order thinking skills tasks related to health topics. However, students' CT ability had never been measured specifically. In addition, students were not accustomed to solving mathematical problems by explicitly using CT-based thinking processes. This condition indicates the need to examine students' CT ability profiles and the factors that influence them. Mumcu et al. (2023)

explain that CT activities based on unplugged computer science can be integrated into mathematics learning in real classroom settings through data collection, data analysis, decomposition, pattern recognition, algorithm design, and testing and improving solutions.

Based on this background, this study addresses the following research questions: (1) What is the profile of computational thinking ability of tenth-grade students at SMK Citra Medika Kota Magelang in mathematics learning? (2) What factors influence students' computational thinking ability in mathematics learning? The study aimed to describe the computational thinking ability profile of tenth-grade students at SMK Citra Medika Kota Magelang in mathematics learning and to identify the factors influencing this ability. The novelty of this study lies in its context: analyzing CT ability among health-vocational high school students through contextual mathematics problems on arithmetic sequences and series. The findings are expected to provide insights for teachers in designing more focused mathematics learning to develop students' CT ability, particularly in health-related vocational contexts. This focus is also supported by recent evidence showing that computational thinking has a positive and significant effect on vocational students' mathematical complex problem-solving ability and should be explicitly integrated into vocational curricula to prepare students for workplace demands (Ardianto et al., 2026).

■ METHOD

Research Design

This study used a descriptive qualitative approach. This approach was selected because the study focused on describing students' computational thinking ability profiles in depth based on test results, open-ended questionnaires, and interviews. The descriptive qualitative design enabled the researcher to reveal students' thinking processes when solving contextual mathematics problems related to health-vocational situations.

Participants and Context

The study was conducted at SMK Citra Medika Kota Magelang with students of Class X Nursing 4. A total of 30 students participated in the CT ability test and completed an open-ended questionnaire. From these 30 students, six students were selected as the main research subjects using purposive sampling. The six subjects represented three CT ability categories: two students in the high category, two students in the medium category, and two students in the low category. Subject selection considered students' CT test results, response completeness, clarity of solution processes, communication ability, and willingness to participate in interviews.

Prior to data collection, this study obtained formal permission from the school administration of SMK Citra Medika Kota Magelang through an official research permit letter. Students' participation in the CT ability test, questionnaire, and interviews was voluntary, and students were informed of the study's purpose and procedures beforehand. To protect participants' privacy, the six main subjects were referred to using anonymous codes (R1, R2, S1, S2, T1, T2) rather than their real names.

Data Collection Instruments

The research instruments consisted of a CT ability test, an open-ended questionnaire, and an interview guide. The CT ability test was developed based on four indicators: decomposition, abstraction, pattern recognition, and algorithmic thinking. The indicators used to analyze students' CT ability are presented in Table 1.

Table 1. Computational thinking ability indicators used in the study

Indicator	Description of student activity
Decomposition	Breaking a problem into smaller parts and determining important information needed to solve it.
Abstraction	Filtering relevant information and ignoring information that is not needed in the solution process.
Pattern recognition	Identifying regularities or changes in data that appear in contextual mathematics problems.
Algorithmic thinking	Arranging solution steps sequentially, logically, and systematically to obtain an accurate answer.

Each indicator was scored using a scoring rubric to determine the extent to which students fulfilled it. Decomposition, abstraction, and pattern recognition were scored on a 0–2 scale, while algorithmic thinking was scored on a 0–3 scale, as shown in Table 2.

Table 2. Scoring rubric for computational thinking indicators

Indicator	Score	Description of student activity
Decomposition	2	Breaks the problem into relevant components
	1	Breaks down only part of the components
	0	Does not break down the problem, or states it only in general terms
Abstraction	2	Excludes all irrelevant information
	1	Excludes only part of the irrelevant information
	0	Includes irrelevant information
Pattern recognition	2	Identifies the sequence pattern correctly
	1	Identifies a pattern but with incorrect order/precision
	0	Does not identify any pattern
Algorithmic thinking	3	Writes formula, steps, and final result completely and correctly
	2	Writes some correct steps but wrong result, or correct formula with incorrect/unsystematic steps
	1	Shows partial effort (formula, steps, or result) with many errors
	0	No effort shown, or all incorrect

The test items were contextual mathematics problems on arithmetic sequences and series related to health situations. The open-ended questionnaire was used to obtain information about factors influencing students' CT ability. In contrast, the interviews explored students' thinking processes, solution strategies, and difficulties in solving the problems in greater depth.

Although the test consisted of only two items, each item was designed as a multi-step contextual problem requiring students to progressively decompose the problem, abstract relevant information, recognize numerical patterns, and construct a systematic solution procedure. Thus, each item was intended to elicit evidence for all four CT indicators within a single problem-solving process, rather than assessing indicators through separate items.

Before being used in the main study, the test instrument was analyzed for feasibility. The content validity results showed that the test and questionnaire obtained a V value of 0.74, which was categorized as medium. The construct validity results showed that both test items were valid, with correlation coefficients of 0.8835 and 0.9143. The instrument reliability was categorized as high, with a value of 0.759. In addition, the difficulty indices of the two items were in the medium category (0.42 and 0.43), while the discrimination indices were in the good category (0.475 and 0.563). These results indicate that the instrument was suitable for collecting data on students' CT ability.

Data collection was conducted in three stages. The first stage involved administering the CT ability test and open-ended questionnaire to 30 students in Class X Nursing 4. The second stage was conducting interviews with the six subjects selected based on their CT ability categories. The third stage was data analysis based on the test results, questionnaire responses, and interviews. Test data were used to determine the achievement of CT indicators, questionnaire data were used to identify factors influencing CT ability, and interview data were used to strengthen and clarify the test and questionnaire results.

Data Analysis Procedure

Data were analyzed through data reduction, data display, and conclusion drawing. Students' computational thinking categories were determined by the number of indicators met, where a score of 2 for decomposition, abstraction, and pattern recognition, or a score of 3 for algorithmic thinking, was considered satisfactory. Students who met all four indicators were categorized as high, those who met two to three indicators as medium, and those who met none or only one indicator as low. This rule was applied to all 30 students before purposive sampling of the six subjects. Data reduction was carried out by selecting relevant information from students' answer sheets, questionnaire responses, and interview transcripts based on CT ability indicators. Data were displayed in descriptive narratives and tables to show students' CT ability profiles in each category clearly. Conclusions were drawn by comparing the results of the tests, questionnaires, and interviews. Data validity was examined through triangulation by comparing data from tests, questionnaires, and interviews from the same subjects.

RESULT AND DISCUSSION

The results showed that tenth-grade students' computational thinking ability at SMK Citra Medika Kota Magelang varied across low, medium, and high categories. This variation was reflected in the achievement of four CT indicators, namely decomposition, abstraction, pattern recognition, and algorithmic thinking. Students' computational thinking ability was classified based on the number of indicators each student achieved.

The distribution of students based on their computational thinking ability category is presented in Figure 1. The figure illustrates the proportion of students classified as having low, medium, and high computational thinking ability.

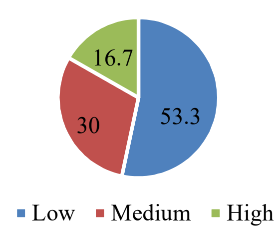

Figure 1. Distribution of students' CT ability

Based on Figure 1, 53.3% of students were categorized as having low computational thinking ability, 30% as having medium ability, and 16.7% as having high ability. These findings indicate that most students had not yet consistently demonstrated all computational thinking indicators. The relatively large proportion of students in the low category suggests that further analysis is needed to identify which computational thinking indicators students achieved most and least.

To provide a more detailed description of students' computational thinking ability, the achievement of each computational thinking indicator was analyzed based on students' responses to the two questions administered. The analysis focused on four indicators: decomposition, abstraction, pattern recognition, and algorithmic thinking. The results of the analysis are presented in Table 3.

Based on the test results, questionnaire responses, and interviews, students in the low category had not optimally fulfilled the CT indicators. In the decomposition indicator, students in this category were able to write some important information, such as the initial value, increment, number of days, or initial stock. However, they still mixed relevant and irrelevant information. For example, in the problem about a patient's walking exercise, students still listed the patient's age and blood pressure as important information. However, they did not use these data in the calculation. This finding indicates that students had begun to demonstrate decomposition by identifying the numerical components of the problem, but had not yet demonstrated abstraction, as they were unable to filter out

Table 3. Students' achievement of computational thinking indicators

Indicators	Question 1						Question 2					
	R1	R2	S1	S2	T1	T2	R1	R2	S1	S2	T1	T2
Decomposition	1	1	2	2	2	2	1	1	2	2	2	2
Abstraction	0	0	2	2	2	2	0	0	2	2	2	2
Pattern recognition	0	0	2	2	2	2	0	0	2	2	2	2
Algorithmic thinking	1	1	2	2	3	3	1	1	2	2	3	3

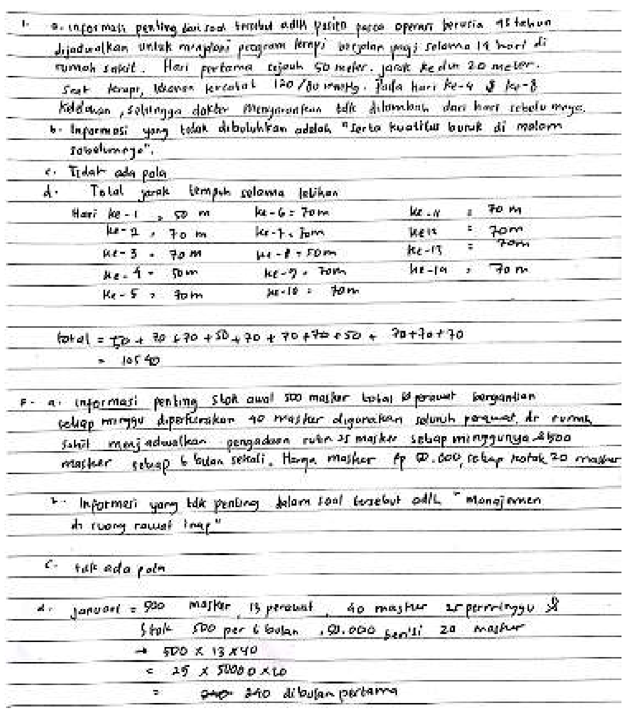
1\. a. informasi penting dari soal tersebut adlh pasien pasca operasi berusia 45 tahun dijadwalkan untuk menjalani program terapi berjalan pagi selama 14 hari di rumah sakit. Hari pertama sejauh 50 meter. jarak kedua 20 meter. Saat terapi, tekanan tercatat 120/80 mmHg. pada hari ke-4 & ke-8 [illegible], sehingga dokter menyarankan tdk ditambah dari hari sebelumnya.
b. Informasi yang tidak dibutuhkan adalah "serta kualitas buruk di malam sebelumnya".
c. Tidak ada pola
d. Total jarak tempuh selama latihan
Hari ke-1 = 50 m, ke-2 = 70 m, ke-3 = 70 m, ke-4 = 50 m, ke-5 = 70 m
ke-6 = 70 m, ke-7 = 70 m, ke-8 = 50 m, ke-9 = 70 m, ke-10 = 70 m
ke-11 = 70 m, ke-12 = 70 m, ke-13 = 70 m, ke-14 = 70 m
total = 50 + 70 + 70 + 50 + 70 + 70 + 70 + 50 + 70 + 70 + 70
= 10540
2\. a. informasi penting stok awal 500 masker total 13 perawat bergantian setiap minggu diperkirakan 40 masker digunakan seluruh perawat, dr rumah sakit menjadwalkan pengadaan rutin 25 masker setiap minggunya & 500 masker setiap 6 bulan sekali. Harga masker Rp 50.000, setiap kotak 20 masker
b. Informasi yang tdk penting dalam soal tersebut adlh "Manajemen di ruang rawat inap"
c. tdk ada pola
d. januari = 500 masker, 13 perawat, 40 masker, 25 perminggu
stok 500 per 6 bulan, 50.000 berisi 20 masker
→ 500 × 13 × 40
= 25 × 50000 × 20
= ~~[illegible]~~ 340 di bulan pertama

Figure 2. Low-category student answer results

irrelevant information such as the patient's age and blood pressure or select the information that was truly needed.

The greatest difficulties among students in the low category appeared in abstraction and pattern recognition. In the abstraction indicator, students in this category tended to consider all information in the problem important. In the interview, one low-category student stated, "I do not know, Sir," when asked to identify information that was not used in the calculation. This statement indicates that students are not yet able to filter out irrelevant information. Regarding the pattern recognition indicator, students in the low-ability category were unable to identify regularities in the problems, even though the problems contained ascending or descending patterns. One student wrote that there was no pattern in the problem, which subsequently led to the selection of an inappropriate problem-solving strategy. This affected their algorithmic thinking skills because the students lacked a solid foundation for systematically formulating solution steps.

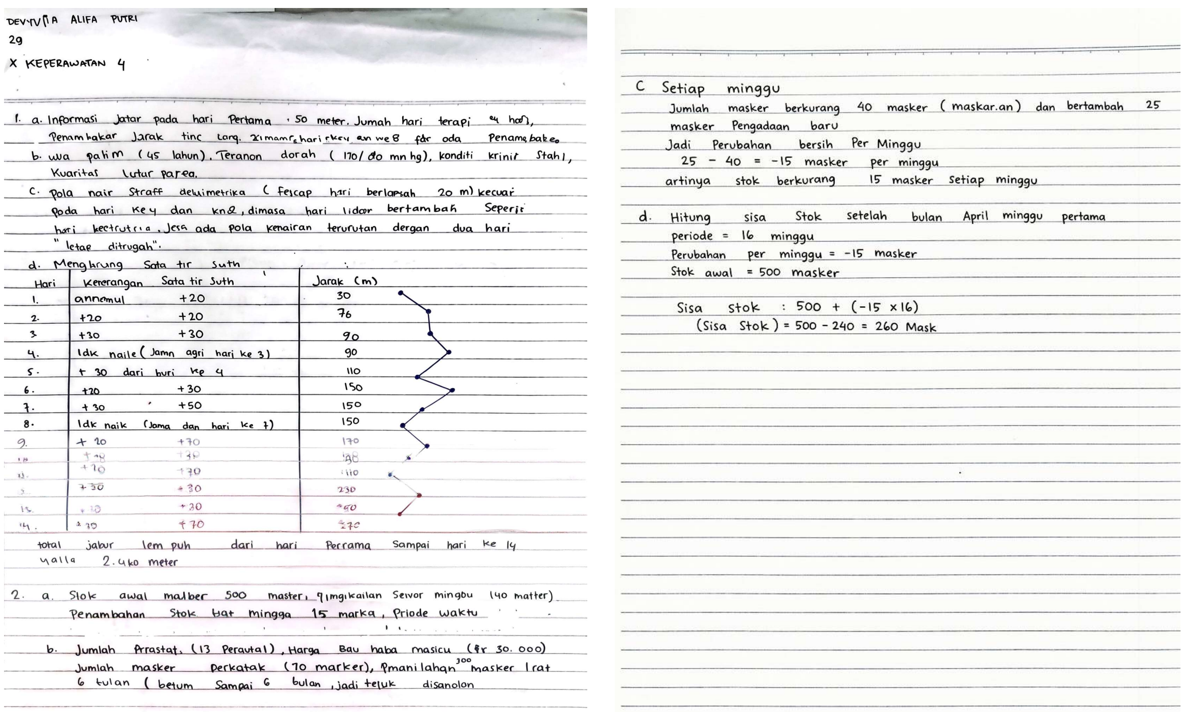

Figure 3. Medium category student answer results

Students in the medium category demonstrated better computational thinking (CT) skills compared to students in the low category. Regarding the decomposition indicator, students in the medium category were already able to identify the key information needed to solve problems. They could also select relevant information and recognize patterns within the problems. In an interview, one student in the medium category stated that he first reads the information he considers important and then incorporates it into the problem-solving process. This indicates that students in the medium category already have an initial strategy for understanding problems. However, they still experience difficulties with algorithmic thinking, particularly when formulating lengthy solution procedures involving multiple calculation steps.

Students in the medium category struggle to formulate steps or perform complex calculations. They are able to recognize patterns, but they are not yet able to translate those patterns into efficient and accurate problem-solving procedures. In an interview, a student in the medium category stated, “Yes, and I have to be careful.” This statement indicates that the student recognizes the importance of precision but still needs practice in formulating appropriate and systematic problem-solving steps. Therefore, students in the medium category can be said to have met most of the CT indicators but still need reinforcement in algorithmic thinking

Figure 4. High category student answer results

Students in the high category fulfilled all CT indicators more consistently. In decomposition, they broke the problem into smaller parts and identified the important information used in the solution. In abstraction, they ignored irrelevant information. In pattern recognition, they identified regularities in the problems, including special conditions that affected the final result. In algorithmic thinking, they arranged solution steps logically and systematically and obtained correct answers. These findings indicate that high-category students not only understood the content of the problems but also connected information, patterns, and mathematical procedures in an integrated way.

The differences in ability across categories indicate that CT develops gradually. Students in the low category tended to remain at the surface level of understanding the problems, so the information they wrote was not yet fully focused. Students in the medium category understood the problem structure but were not yet stable in arranging solution procedures. Students in the high category were able to integrate information, patterns, and solution procedures more completely. The findings also support Subramaniam et al. (2022), who emphasized that CT in mathematics learning helps students solve complex problems systematically. Nordby et al. (2024) also explained that using CT tools and activities in mathematics classrooms can help students understand mathematical concepts. However, their effectiveness still depends on the suitability of the tools, the design of the activities, and the teacher's role in the learning process.

The findings among low-category students show that abstraction and pattern recognition were the most difficult indicators. Difficulties in abstraction made students unable to distinguish main information from supporting information. As a result, they had difficulty identifying the mathematical structure of the problems. This finding aligns with Mohd Rosli & Mohd Matore (2023), who found that vocational students still faced challenges in understanding the fundamentals of CT. Furthermore, students' difficulties in recognizing patterns indicate that contextual problems should not only be designed as calculation exercises but also as a means to train students to explicitly analyze problem structure. For students in the medium category, the difficulty lies in the algorithmic thinking indicator. These students are already able to identify information and patterns, but they struggle to formulate systematic solution steps. This finding indicates that mastery of the initial CT indicators does not automatically ensure successful problem solving if students cannot yet design coherent procedures. This is consistent with Kaup et al. (2023), who stated that CT and mathematical understanding are interrelated; therefore, CT reinforcement needs to be carried out alongside reinforcement of mathematical concepts. In other words, students should be trained not only to find patterns but also to write solution procedures based on those patterns.

For students in the high category, meeting all CT indicators shows that their thinking was more structured. These students could understand information, filter data, identify patterns, and construct solution algorithms accurately. This finding is consistent with Tiffani et al. (2025), who stated that students with good computational ability can write relevant information, recognize patterns, use correct steps, and obtain accurate final results. This finding is also supported by Chong & Chong (2024), who found that students with high CT ability demonstrated mastery of all CT indicators.

In addition to CT ability profiles, this study also identified factors that influenced students' CT ability. These factors consisted of internal and external factors. Internal factors included prerequisite mathematical knowledge, learning motivation, and learning independence. External factors included the learning environment and the use of learning resources. A summary of the factors influencing students' CT ability is presented in Figure 5.

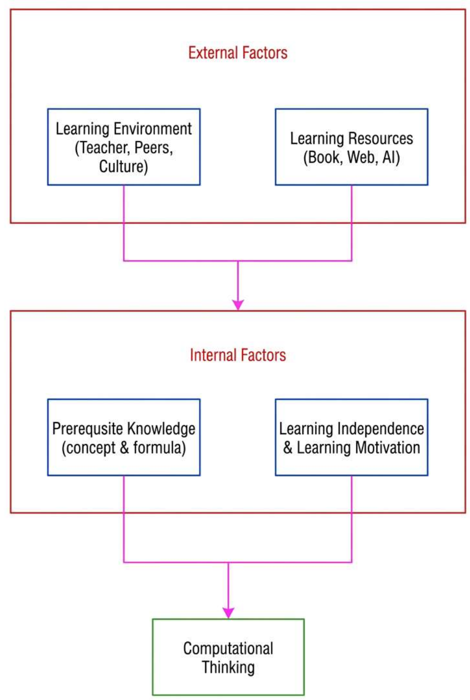

Figure 5. Factors influencing students' computational thinking ability

Prerequisite mathematical knowledge was an important factor in students' CT ability. Questionnaire data showed that most students understood the basic concepts of arithmetic sequences and series, although some students still forgot formulas or solution procedures. Twenty students stated that they understood the basic concepts, six stated that they understood the concepts but still forgot the formulas or procedures, and a small number stated that they only slightly understood or did not yet understand the material. In addition, 12 students stated that their previous learning experiences helped them understand the problems. These findings indicate that mastery of prerequisite material helps students determine solution strategies, whereas weak conceptual understanding makes it difficult for students to carry out CT processes optimally. This finding aligns with Lee et al. (2023), who showed that mathematics learning helps predict students' CT competence, and Kaup et al. (2023), who emphasized that CT can strengthen mathematical understanding.

Learning motivation also influenced students' CT ability. Most students responded positively to the problems given. Seventeen students felt challenged when solving the problems, while six students felt both happy and challenged. Students with positive motivation tended to continue trying to solve the problems even when they faced difficulties. However, some students felt pressured because they considered mathematics difficult. One low-category student stated, "Because I cannot do mathematics," when asked why the student felt pressured. This statement indicates that low self-confidence can hinder students from trying solution strategies. This finding is consistent with Ye et al. (2022), who stated that students' perceptions, motivation, and performance are related to CT. Fagerlund et al. (2022) also found that learning motivation plays a role in CT learning.

Learning independence was another factor supporting CT ability. When facing problems they could not solve immediately, some students tried to find solutions independently, looked for similar examples, tried other strategies, or asked teachers and peers. This learning independence is related to students' ability to regulate their own thinking processes. In CT, students need to actively decompose problems, select information, recognize patterns, and arrange solution steps. Therefore, students who have learning initiative tend to be more capable of developing CT processes. This finding is consistent with Chen et al. (2023), who showed that self-regulation, time management, and help-seeking behavior play roles in CT learning.

The learning environment also influences students' CT ability. According to Mills et al. (2025), a learning environment designed with appropriate pedagogical strategies, collaborative activities, and the integration of coding or computational thinking across the curriculum can support the development of students' CT skills and affect their learning outcomes. The learning environment also influenced students' CT ability. The teacher's role helped students understand concepts, direct solution strategies, and habituate systematic thinking processes. Peers also supported learning through discussion and question-and-answer activities. However, a less conducive classroom atmosphere could interfere with students' focus. This condition indicates that CT development depends not only on individual ability but also on support from the learning environment. Liu et al. (2024) emphasized that teacher support is important in integrating CT into K-12 learning. Therefore, teachers need to create learning situations that give students opportunities to analyze problems, discuss ideas, and organize solutions in a directed manner. Xing & Zeng (2025) also stated that the smart classroom environment, as a technology-based learning environment, plays a role in developing students' CT abilities, especially when students' ICT literacy is supported through the purposeful use of technology in learning.

Learning resources were external factors that also supported CT ability. Students used various learning resources, such as textbooks, teacher notes, YouTube, Google, and AI-based platforms. YouTube helped students review material through visual explanations, while search engines and AI platforms provided additional explanations. The use of digital learning resources can help students broaden their understanding when used appropriately and purposefully. Weng et al. (2024) showed that integrating artificial intelligence and CT in educational contexts can support students' learning outcomes when designed appropriately. However, the use of digital resources should still be guided so that students do not merely obtain answers but also understand the thinking processes and solution steps.

Based on the overall findings, mathematics learning in health-vocational schools needs to explicitly train CT processes. Teachers can habituate students to write down known and requested information, select relevant information, ignore irrelevant information, recognize patterns of change, and arrange solution steps sequentially. Teachers can conduct this practice through contextual health-related problems, such as drug dosage calculations, patient walking progress, mask stock management, or simple health data analysis. Thus, students not only learn to solve math problems but also develop ways of thinking relevant to their vocational fields. Lu et al. (2025) state that support from teachers, families, and peers positively affects students' CT abilities; emotional support from teachers is one of the factors that contributes most to students' creativity, problem-solving skills, and collaboration.

The difficulties experienced by students in the low-ability category in abstraction and pattern recognition indicate the need to strengthen metacognition in mathematics learning. Zhang et al. (2024) explained that CT mediates the relationship between metacognition and mathematical modeling skills among secondary school students. This means that when students can monitor information, evaluate strategies, and control their thinking processes, they are more likely to construct problem-solving models in a directed manner. Gunawan et al. (2025) also found that students with high and medium self-efficacy tend to complete the stages of CT more effectively. In contrast, students with low self-efficacy require reinforcement at the representation stage before progressing to algorithm construction. Therefore, students who are not yet able to filter information and recognize patterns should receive scaffolding in the form of guiding questions, visual representations, and exercises that require them to write down the reasons for selecting particular information.

In the context of health vocational schools, the strengthening of CT is theoretically relevant to the characteristics of vocational education, which emphasizes readiness to perform professional tasks. Hermans et al. (2024) emphasized that integrating CT into vocational education and training is important because the modern workplace requires digital literacy, problem-solving skills, and the ability to use technology efficiently. However, the present study did not directly explore students' perceptions of how CT relates to nursing tasks; the contextual design of the test items involving patient data, medication stock, and health-related measurements points toward this potential connection. Mathematics problems based on health contexts may therefore bridge mathematical concepts and the demand for systematic thinking in vocational settings.

The implication of this study is that CT assessment in mathematics education should not focus solely on final answers, but also on students' thought processes. For students in the low category, teachers need to provide basic practice in selecting relevant information and recognizing simple patterns. Meanwhile, for students in the medium category, teachers need to strengthen algorithmic thinking by guiding students to organize their problem-solving steps systematically. For students in the high category, teachers can provide more complex problems so that students can develop more efficient problem-solving strategies. Through these measures, mathematics learning in health vocational schools can become more meaningful by connecting mathematical concepts, CT skills, and the students' vocational contexts.

CONCLUSION

The computational thinking skills of tenth-grade students at SMK Citra Medika in Magelang City in mathematics instruction were categorized as high, medium, and low. Students in the high category consistently met the indicators of decomposition, abstraction, pattern recognition, and algorithmic thinking. Students in the medium category met the indicators of decomposition, abstraction, and pattern recognition but still had difficulty formulating systematic algorithmic procedures. Meanwhile, students in the low category have not met all indicators, whether in selecting relevant information, recognizing patterns, or formulating logical problem-solving steps. Students' CT skills are associated with prerequisite mathematical knowledge, learning motivation, independent learning, the learning environment, and the use of learning resources. These findings suggest that mathematics learning in health-vocational schools should emphasize CT-oriented activities through contextual problems, guided problem analysis, and systematic solution planning to strengthen students' mathematical problem-solving ability and vocational readiness.

However, this study has several limitations. First, it was conducted in only one health-vocational high school and involved a limited number of main subjects; therefore, the findings cannot be generalized to all vocational high school students. Second, the analysis focused only on contextual mathematics problems involving arithmetic sequences and series, so students' CT ability in other mathematical topics or vocational contexts may show different patterns. Third, this study did not directly explore students' own perceptions of how their computational thinking relates to real vocational tasks. Future researchers are encouraged to involve broader and more diverse participants, apply mixed-method or quantitative designs, and examine CT ability across different mathematics topics and vocational fields. Further studies may also develop and test CT-oriented learning models or learning media to improve students' decomposition, abstraction, pattern recognition, and algorithmic thinking.

DECLARATION OF GENERATIVE AI USAGE IN THE WRITING PROCESS

During the writing of this manuscript, the author(s) employed Grammarly to assist with language refinement/proofreading. The author(s) have reviewed and edited the content generated by this tool and assume full responsibility for the content of the published article.

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