Journal of Education and Training Studies
Vol. 14, No. 1; January 2026
ISSN 2324-805X E-ISSN 2324-8068
Published by Redfame Publishing
URL: http://jets.redfame.com

# How Does Computational Thinking Affect Mathematical Complex Problem-solving?

Muhammad Irvan Ardianto[1], Megita Dwi Pamungkas[1], Nina Agustyaningrum[1]

[1]Department of Mathematics Education, Universitas Tidar, Jawa Tengah, Indonesia

Correspondence: Megita Dwi Pamungkas, Department of Mathematics Education, Universitas Tidar, Jawa Tengah, Indonesia

Received: November 3, 2025 Accepted: December 5, 2025 Online Published: December 11, 2025

doi:10.11114/jets.v14i1.8130 URL: https://doi.org/10.11114/jets.v14i1.8130

**Abstract**

Vocational High School graduates represent the highest proportion of unemployment in Indonesia. One key factor is the mismatch between graduates' competencies and industry demands, particularly in complex problem-solving skills. Computational thinking has great potential to enhance such abilities; however, limited studies have examined its direct effect on mathematical complex problem-solving in vocational education. This study aimed to determine the significance and magnitude of the effect of computational thinking on students' mathematical complex problem-solving abilities and to explore how students with different levels of computational thinking approach complex mathematical problems. A mixed-methods approach with a sequential explanatory design was applied, involving 99 informatics engineering students in the quantitative phase and 15 purposively selected students in the qualitative phase. Simple linear regression revealed a positive and significant effect of computational thinking on complex problem-solving, accounting for 69.2% of the variance. Qualitative findings showed that students with higher computational thinking demonstrated systematic and logical reasoning through structured problem-solving processes, whereas those with lower levels relied on trial and error. The findings underscore the importance of explicitly integrating computational thinking into vocational curricula to enhance students' complex problem-solving abilities and prepare them for industrial demands.

**Keywords:** computational thinking, complex problem-solving, mathematics, vocational education, informatics engineering

## 1. Introduction

Vocational High Schools in Indonesia are secondary education institutions that focus on developing students' vocational skills. According to the Regulation of the Minister of Education and Culture No. 34 of 2018 concerning the National Standards for Vocational High Schools/Madrasah Aliyah Vocational Schools, the primary goal of vocational education is to produce a skilled workforce that meets the demands of business and industry while enabling students to develop their potential in adopting and adapting to advances in science, technology, and the arts. Vocational education is designed to provide students with practice-based learning experiences, allowing them to enter the workforce or continue to higher education after graduation (Altan & Altıntas, 2017; Nyström & Ahn, 2025). However, data from Statistics Indonesia (2024) reveal that vocational school graduates have the highest open unemployment rate at 9.01 %. According to Frisnoiry, Sihotang, Indri and Munthe (2024), this high rate is due to the gap between the qualifications of vocational school graduates and the needs of the labour market. Many industries report that graduates lack both technical and soft skills, such as communication, teamwork, and complex problem-solving abilities, which are essential in modern professional environments (Hegde & Kavade, 2025).

One of the most crucial competencies required in today's world of work is the ability to solve complex problems (Molnár & Greiff, 2023; World Economic Forum, 2020). Complex problem-solving refers to an individual's capacity to identify complex issues, comprehend and analyse relevant information, and formulate effective solutions (Funke, 2021; OECD, 2014). This skill is highly valued across managerial, professional, and technical occupations that are rapidly evolving and demand high levels of competence. It has also been recognised as one of the key skills required to thrive in dynamic and continuously changing work environments (Greiff, Stadler, Sonnleitner, Wolff & Martin, 2015).

Complex problem-solving is, therefore, an essential skill for vocational students to meet industrial demands. However, empirical evidence shows that this ability has not yet developed optimally among students. In general, vocational students' problem-solving skills remain low (Mailisman, Ikhsan & Hajidin, 2020; Yustiana, Kusmayadi & Fitriana, 2021). This finding is reinforced by Anggraini, Pratowo and Sudibyo (2022), who reported that vocational students' ability to solve complex problems is categorised as very low, with an average score of only 24.9 out of 100. This is ironic, considering that vocational students are specifically prepared to face real-world challenges in the workplace, which are often complex and demand advanced problem-solving skills. Therefore, it is crucial to make deliberate efforts to enhance vocational students' ability to solve complex problems.

One potential cognitive approach to improve problem-solving skills is computational thinking (Celik, 2023; Lehmann, 2025; Yadav, Ocak & Oliver, 2022). Computational thinking is not limited to programming or computer science; it is a way of reasoning that enables individuals to understand complex problems and solve them efficiently through principles and methods derived from computer science (Arfé, Vardanega & Ronconi, 2020; Salmon-Mordekovich, 2024; Shute, Sun & Asbell-Clarke, 2017; Wing, 2008). This framework includes the cognitive processes of decomposition, abstraction, pattern recognition, and algorithmic thinking (Bouck, Sands, Long & Yadav, 2021; Dehbozorgi & Roopaei, 2024; Huang & Looi, 2021; Pirzado, Ahmed, Hussain, Ibarra-Vázquez & Terashima-Marin, 2025; Yeni, Nijenhuis-Voogt, Saeli, Barendsen & Hermans, 2024). Computational thinking can be applied not only in computing but also across various disciplines, including education (Araya, Isoda & Moris, 2021; Denning & Tedre, 2021; Tomperi, 2020). By cultivating computational thinking, students can enhance cognitive abilities such as analysis, planning, and evaluation, ultimately leading to more effective and efficient problem-solving (Montuori, Gambarota, Altoé & Arfé, 2024; Salwadila & Hapizah, 2024). In mathematics education, computational thinking has also been shown to improve students' problem-solving performance (Helsa, Juandi & Turmudi, 2023; Wahab, Talib, Razali & Kamarudin, 2021).

Several studies have demonstrated a relationship between computational thinking and complex problem-solving in various contexts—for example, algorithmic tasks such as the Tower of Hanoi among computer science students (Fei, Dong & Fei, 2025), the development of computational thinking-based learning models to enhance problem-solving among pre-service computer teachers (Sukkamart, Sermsri, Kantathanawat, Nakwijit & Meekhobtong, 2024), and the use of Scratch programming to improve students' problem-solving abilities (Aminah, Sukestiyarno, Cahyono & Maat, 2023). These findings highlight the potential of computational thinking to foster complex problem-solving ability. However, most previous studies have been conducted at the tertiary level or within specific intervention-based settings.

A bibliometric analysis using VOSviewer (Figure 1) revealed that although "computational thinking" and "complex problem-solving" are conceptually related, these two terms show minimal direct association with "vocational education." Consequently, there is a lack of studies that explicitly examine the direct effect of computational thinking on complex problem-solving ability among vocational high school students.

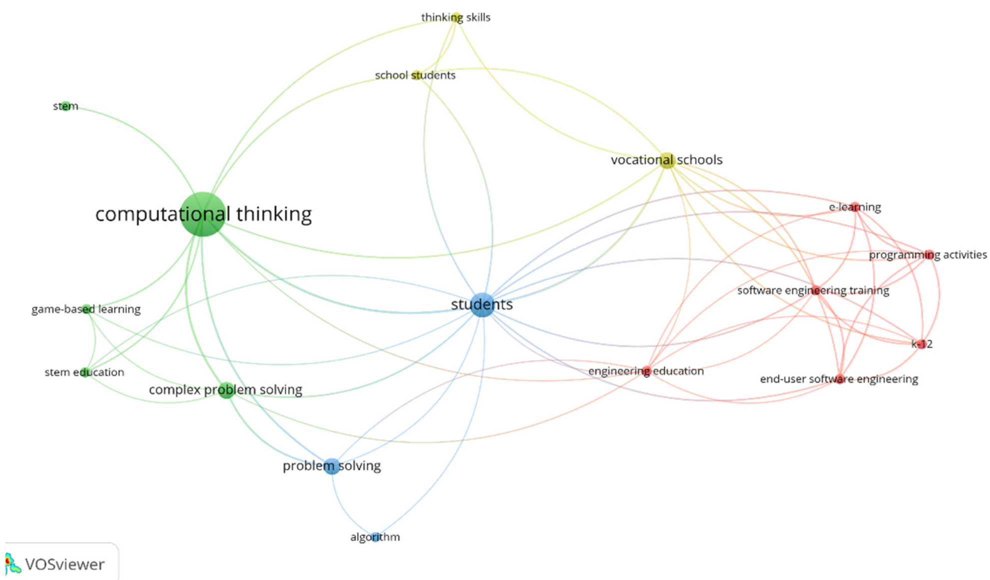



Figure 1. Visualization of keyword co-occurrence related to CT, CPS, and vocational education (2015–2025)

Students majoring in Informatics Engineering are a particularly relevant group to be studied in the context of computational thinking and complex problem-solving. This specialisation focuses on mastering computer science concepts, including programming, computational logic, algorithms, and software development. Through programming practice and algorithmic learning, Informatics Engineering students are accustomed to breaking down problems into systematic steps and identifying solution patterns, which indirectly develop their computational thinking skills (Hsu, 2025; Lee, Francom & Nuatomue, 2022). Moreover, students from Informatics Engineering programmes have been found to possess higher levels of computational thinking compared to their peers from other technical fields (Çetin, 2025; Pirzado et al., 2025). This finding is consistent with interviews conducted with mathematics and vocational teachers at one of the vocational schools, who noted that Informatics Engineering students tend to think more systematically when solving problems than students from other departments.

Based on the explanation above, this study is crucial in providing empirical evidence on the effect of computational thinking on complex problem-solving within the context of vocational education. The findings are expected to contribute to the development of instructional strategies that foster computational thinking while simultaneously improving students' complex problem-solving skills. Specifically, this study aims to (1) examine the significance and magnitude of the effect of computational thinking on students' complex problem-solving abilities, and (2) explore students' problem-solving processes according to their levels of computational thinking (high, medium, and low). Accordingly, it is hypothesised that computational thinking has a significant positive effect on students' complex problem-solving ability.

## 2. Literature Review

### *2.1 Computational Thinking in Education*

Computational thinking (CT) is widely recognised as a fundamental skill for the 21st century, described as the thought processes involved in formulating problems so that their solutions can be effectively carried out by an information-processing agent (Wing, 2006). In mathematics education, CT offers a cognitive framework that supports logical reasoning and structural analysis (Shute et al., 2017). Based on the framework adapted for this study (Bouck et al., 2021; Dehbozorgi & Roopaei, 2024; Huang & Looi, 2021), CT comprises four key dimensions: decomposition, abstraction, pattern recognition, and algorithmic thinking.

The first dimension, decomposition, involves breaking down complex problems into smaller, more manageable components. As noted by Suarsana et al. (2025) this process is critical in mathematics to simplify multi-layered problems into solvable units. Closely related is abstraction, which refers to the ability to identify relevant information while ignoring non-essential details. Richardo et al. (2025) emphasise that abstraction allows learners to focus on the core mathematical structure, while Kelly and Gero (2021) highlight its role in filtering out noise in design contexts. The third dimension, pattern recognition, requires learners to identify similarities, trends, or relationships within data. Wu, Asmara, Huang and Permata Hapsari (2024) describe this as recognising unique characteristics, which Acosta, Alsina and Pincheira (2024) argue is essential for generalising solutions. Finally, algorithmic thinking entails developing a sequence of logical steps to reach a solution (Huang & Looi, 2021; Pirzado et al., 2025). Lehmann (2024) defines this further as a systematic reasoning process that creates reproducible procedures for problem resolution.

### *2.2 Complex Problem-Solving*

Complex problem-solving (CPS) is distinct from routine problem-solving as it deals with ill-defined problems where information is incomplete, the environment is dynamic, and multiple variables are interrelated (Funke, 2012). According to the framework proposed by Funke (2019), CPS includes five distinct features: complexity, connectivity, dynamics, intransparency, and polytely. Complexity arises from the high number of variables and data points involved in the situation. Connectivity refers to the intricate relationships between these variables, where a change in one element often impacts others. The problem is also dynamic, meaning the situation may change over time or as a direct result of the solver's actions. Furthermore, CPS involves intransparency, where not all necessary information is immediately available, requiring the solver to make inferences or actively seek data. Lastly, polytely describes the presence of multiple, and sometimes conflicting, goals that the solver must prioritise effectively.

### *2.3 The Interrelation between CT and Mathematical Complex Problem-Solving*

In mathematics, problem-solving has traditionally been grounded in the heuristics proposed by Polya (1945), which consist of four stages: understanding the problem, devising a plan, carrying out the plan, and looking back. While these stages provide a foundational structure, the specific nature of complex problem solving—characterised by dynamic and ill-defined constraints—requires a more granular cognitive approach. This study proposes that CT skills serve as the specific cognitive mechanism to navigate the features of CPS defined by Funke (2019).

The connection between CPS features and CT dimensions is evident throughout the problem-solving process. Specifically, the feature of polytely, which involves managing multiple and sometimes conflicting goals, requires learners to employ decomposition to break down these objectives into smaller, manageable sub-problems for prioritisation. Similarly, handling complexity and intransparency relies heavily on abstraction; this dimension enables students to filter out irrelevant contextual noise and logically infer missing data to construct a coherent mathematical model. Furthermore, to master connectivity and dynamics, students utilise pattern recognition to identify how variables influence one another, followed by algorithmic thinking to devise systematic strategies or alternative plans that are adaptable to these changing conditions. Thus, CT provides the specific cognitive tools required to execute the intricate demands of mathematical complex problem-solving effectively.

## 3. Method

This study employed a mixed-methods approach. According to Creswell and Creswell (2018), mixed-methods research is an approach that involves the collection and integration of both quantitative and qualitative data, guided by specific philosophical assumptions and theoretical frameworks. This combination enables researchers to obtain a more comprehensive understanding of a research problem than would be possible through a single method alone.

The design adapted in this study was a sequential explanatory design, in which the quantitative phase is conducted first to obtain general results, followed by the qualitative phase to provide deeper explanations and interpretations of the quantitative findings. This design allows qualitative data to elaborate on or clarify statistical results by exploring participants' perspectives in greater detail. The stages of the research procedure are illustrated in Figure 2.

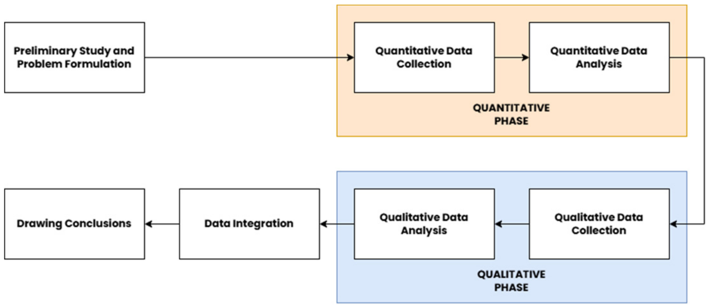



Figure 2. Researcher's research steps

In a sequential explanatory design, the sample size may differ between research phases (Creswell & Creswell, 2018). In the quantitative phase, 99 Year 11 students from a Vocational High School majoring in Informatics Engineering were selected as participants using a cluster random sampling technique. After the quantitative data were collected and analysed, a qualitative phase was conducted to explore more deeply how computational thinking affected complex problem-solving. Fifteen students were purposively selected as qualitative participants based on the categorisation of their computational thinking levels (high, medium, and low) with five students representing each category.

The instruments used in this study consisted of a computational thinking test, a complex problem-solving test, and a semi-structured interview guide. The computational thinking test was developed based on the CT Dimensions (Decomposition, Abstraction, Pattern Recognition, and Algorithmic Thinking). The test consisted of contextual mathematical problems related to social media follower growth, designed to assess learners' ability to demonstrate systematic and logical reasoning. The complex problem-solving test was developed based on the CPS framework (Complexity, Connectivity, Dynamics, Intransparency, and Polytely) discussed in the Literature Review. The test consisted of open-ended, real-world contextual tasks centred on the planning and construction of a school gazebo. The task required learners to engage in planning, calculation, and decision-making processes. The problem was classified as complex because it involved multiple goals that required prioritisation, incomplete or implicit information, and interrelated variables influencing the final outcome (Pamungkas, Waluya & Mariani, 2023). The semi-structured interview guide consisted of open-ended questions aimed at exploring students' problem-solving strategies, difficulties encountered, and the logical reasoning they employed in completing the tasks.

Prior to use, the instruments were evaluated for content validity and construct validity. Expert validation indicated that the instruments were valid, with Aiken's V indices of 0.92 for the CT test and 0.86 for the CPS test (Aiken, 1985). Minor revisions were made based on expert suggestions, such as improving the wording of several items to prevent ambiguity and misinterpretation by students. A pilot test was then conducted with 30 students outside the research sample to assess construct validity and reliability. The results showed that all test items had correlation coefficients above 0.344, indicating satisfactory validity. The reliability coefficients (Cronbach's Alpha) were 0.654 for the CT test and 0.711 for the CPS test. According to the reliability coefficient by Guilford (1956), coefficients greater than 0.60 indicate high reliability. Therefore, the instruments were considered valid and reliable for use in the main study.

Data collection was carried out in two phases, beginning with the quantitative phase. Quantitative data were obtained through the administration of the computational thinking and complex problem-solving tests conducted directly in the classroom. The subsequent qualitative phase involved semi-structured interviews with the fifteen students who had been purposively selected as qualitative participants.

The data were analysed using both quantitative and qualitative approaches. Quantitative data were analysed using descriptive statistics to determine the mean and standard deviation of students' scores. These statistics were used to measure students' CT abilities, which were then categorized according to the classification criteria presented in Table 3.

Table 1. Category guidelines for students' computational thinking ability

| Category Achievements Score | Category |
|---|---|
| $N \geq (\bar{x} + SD)$ | High |
| $(\bar{x} - SD) < N < (\bar{x} + SD)$ | Medium |
| $N \leq (\bar{x} + SD)$ | Low |

Source: (Salwadila & Hapizah, 2024)

Description:

N = Student score

$\bar{x}$ = Mean

SD = Standard Deviation

Simple linear regression analysis was employed to examine the significance and magnitude of the effect of computational thinking on complex problem-solving. Qualitative data analysis followed the five-stage procedure outlined by Creswell and Creswell (2018), which included: (1) organising and preparing the data; (2) reading the entire dataset; (3) coding all data; (4) generating detailed descriptions and major themes, and (5) presenting the descriptions and themes in meaningful narrative form. To enhance the validity of findings, methodological triangulation was applied by comparing data from the same participants obtained through different methods—tests and interviews.

## 4. Results

This section presents the findings of the study. Computational Thinking (CT) and Complex Problem-Solving (CPS) scores were analyzed to determine their relationship. The analysis involved descriptive statistics and regression measures, including degree of freedom (df), F-value (F), significance level (Sig.), and correlation coefficient (R). Students were further classified into three groups: high computational thinking skill (HCT), medium computational thinking skill (MCT), and low computational thinking skill (LCT).

### *4.1 Quantitative Results*

#### 4.1.1 Descriptive Statistics of Students' CT and CPS Abilities

A total of 99 students from the Vocational High School (VHS) majoring in Informatics Engineering were administered the CT and CPS tests. Table 4 presents the descriptive analysis results of students' CT and CPS abilities.

Table 2. Descriptive statistics of students' CT and CPS scores

| Variable | Number | Min | Max | Mean | SD |
|---|---|---|---|---|---|
| CT | 99 | 21.42 | 92.85 | 53.82 | 17.57 |
| CPS | 99 | 27.27 | 90.91 | 50.92 | 13.12 |

Based on the results, the mean score of students' CT ability was 53.82 with a standard deviation of 17.57, while the mean score of CPS ability was 50.92 with a standard deviation of 13.12. The average scores of CT and CPS, which fall within the moderate range, indicate that, in general, students' computational thinking and mathematical complex problem-solving abilities are at a medium level.

#### 4.1.2 The effect of CT on CPS

Quantitative analysis was conducted to examine the effect of students' CT on their CPS ability in the Informatics Engineering programme. The results are illustrated in Figure 3.

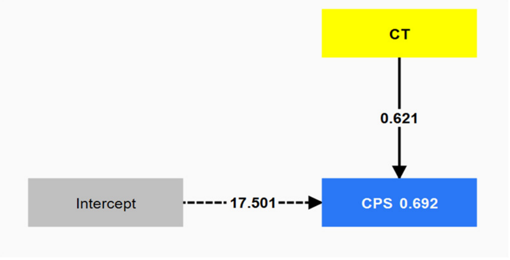



Figure 3. Output analysis from Smart PLS

The regression analysis showed that for every one-point increase in CT score, the CPS score increased by 0.621 points. The positive coefficient of CT indicates a positive relationship, meaning that higher CT scores are associated with higher CPS scores.

Table 3. Summary of the regression model examining the relationship between CT and CPS

| R | R Square ($R^2$) | Adjusted R Square |
|---|---|---|
| 0.831 | 0.692 | 0.689 |

Table 4. ANOVA results for the regression model between CT and CPS

| Model | Sum Square | Df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Regression | 11,655.776 | 1 | 11,655.776 | 217.869 | 0.000 |
| Error | 5,189.405 | 97 | 53.499 | 0.000 | 0.000 |
| Total | 16,845.182 | 98 | 0.000 | 0.000 | 0.000 |

As presented in Table 5, the coefficient of determination ($R^2$) was 0.692, indicating that CT contributed 69.2% to the variance in CPS scores, while the remaining 30.8% was affected by other factors outside the model. Furthermore, the ANOVA results in Table 6 show a significance value (sig.) of 0.000, confirming that CT had a statistically significant effect on CPS.

4.1.3 Categorisation of CT Levels

The data in Table 4 served as the basis for categorising students' CT abilities, as presented in Table 7.

Table 5. Percentage of each category of CT ability among students

| Category Achievements Score | Category | Number of Learners | Percentage |
|---|---|---|---|
| $N \geq (71.4)$ | High | 25 | 25% |
| $(36.3) < N < (71.4)$ | Medium | 51 | 52% |
| $N \leq (36.3)$ | Low | 23 | 23% |

The categorisation shows that 25 students (25%) achieved a high level of CT, with scores above 71.4. A total of 51 students (52%) were in the medium category, with scores ranging between 36.3 and 71.4, while 23 students (23%) were in the low category with scores below 36.3. These findings indicate that the majority of students possessed a moderate level of CT ability.

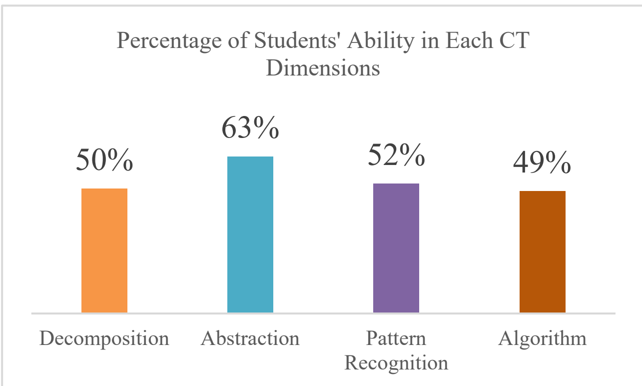



Figure 4. Percentage of students' ability in each CT dimension

The overall performance across CT dimensions was categorised as moderate, although the average percentage for each dimension varied. Figure 4 further illustrates that the Abstraction dimension achieved the highest average score (63%), followed by Pattern Recognition (52%), Decomposition (50%), and Algorithm (49%). These results suggest that while students demonstrated moderate overall CT ability, abstraction skills were the most developed among the four dimensions.

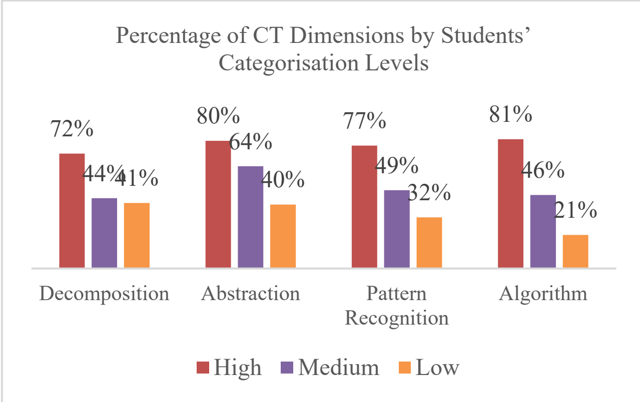



Figure 5. Percentage of CT dimensions by students' categorisation levels

Figure 5 shows the percentage of students' achievement across each Computational Thinking (CT) dimension based on their ability category. The figure indicates a consistent pattern in which students with high CT ability outperform those in the medium and low categories in all four dimensions. Students in the high category achieved the highest percentages in Decomposition (72%), Abstraction (80%), Pattern Recognition (77%), and Algorithm (81%). In contrast, students in the medium category showed moderate performance, with percentages ranging from 44% to 64%, while those in the low category scored the lowest across dimensions, between 21% and 41%. Overall, the figure highlights that performance across all CT dimensions increases proportionally with the level of CT ability.

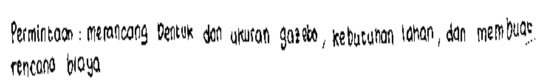
*4.2 Qualitative Results*

The qualitative phase was conducted following the quantitative analysis to provide a deeper explanation of how students with different levels of Computational Thinking (CT) solved complex mathematical problems. Data were obtained through semi-structured interviews with fifteen students representing three CT ability categories: high, medium, and low. The analysis referred to four dimensions of CT (Decomposition, Abstraction, Pattern Recognition, and Algorithmic Thinking).

4.2.1 Subjects with High CT Skill (HCT)

Students categorised as having high CT ability demonstrated relatively strong performance across all CT dimensions, with the highest achievement in Algorithmic Thinking (81%), followed by Abstraction (80%), Pattern Recognition (77%), and Decomposition (72%). Overall, this group exhibited systematic and logical thinking in their approach to solving complex mathematical problems.

In the Decomposition dimension, almost all subjects were able to break down the main problem—such as determining the budget for constructing a school gazebo—into smaller and more structured sub-problems, including calculating the land area, estimating material requirements, and determining the total cost.




**Translation:**

Demands: design the shape and size of the gazebo, land requirements, and prepare a cost plan.

Figure 6. HCT's answer about simplifying the problem

The excerpt below is taken from an interview by The Researcher (R) with an HCT student:

**R** : *The budgeting problem is quite complex. Did you break it into smaller problems?*
**HCT** : *Yes.*
**R** : *Into what parts did you break it?*
**HCT** : *The paving, that's the base — calculating the floor area. Then the roof, which is four triangles. Also, calculating the land area that's bordered.*

In the Abstraction dimension, high-CT students were able to select relevant information (such as land size, 60% proportion, and material prices) while ignoring non-mathematical information, such as the school programme description. They also showed awareness of why certain data were important to the calculation.

<table>
<tr>
<td>
• Informasi yang relevan :<br>
- lahan yang ada 12 x 9 m, namun hanya 60%<br>
. Tinggi gazebo dari lantai ke puncak atap tidak boleh lebih dari 5M<br>
- Pondasi berbentuk persegi / persegi panjang<br>
- lantai gazebo terbuat dari paving blok<br>
- atap menggunakan spandek pasir berbentuk limas segiempat<br>
- Bahan tersedia : 2 kayu jati dengan panjang 6M dengan harga Rp 2.000.000
</td>
<td>
Translation:<br>
Relevant information<br>
• The available area is 12 x 9 m, but only 60%<br>
• The height of the gazebo from the floor to the top of the roof must not exceed 5 m<br>
• The foundation is square/rectangular in shape<br>
• The gazebo floor is made of paving blocks<br>
• The roof uses a four-sided pyramid-shaped sand spandek<br>
• Available materials: two teak wood pieces, each 6 metres long, priced at Rp 2,000,000
</td>
</tr>
</table>

Figure 7. HCT's answer about identifying relevant information

The excerpt below is taken from an interview with an HCT student:

**R** : *In the problem, there's a lot of information. What did you do?*

**HCT** : *I sorted it out, chose what's important.*

**R** : *How did you decide what's important?*

**HCT** : *Based on what's relevant.*

**R** : *How did you know what's relevant or not?*

**HCT** : *From what's needed and what's not.*

**R** : *Needed for what?*

**HCT** : *For the gazebo.*

**R** : *For the calculation too?*

**HCT** : *Yes.*

**R** : *So, if it's not needed for the calculation, it's not important?*

**HCT** : *Yes.*

For the Pattern Recognition dimension, all students recognised relationships among the problem components, such as dimensions, materials, and costs. Some even provided detailed explanations linking mathematical relations to real-world contexts.

<table>
<tr>
<td>
hubungan : jika ukuran<br>
gazebo semakin besar,<br>
maka bahan makin<br>
banyak dibutuhkan dan<br>
biaya semakin besar
</td>
<td>
Translation:<br>
Relationship: the larger the gazebo, the more materials are needed and the higher the cost.
</td>
</tr>
</table>

Figure 8. HCT's answer about the pattern recognition

The excerpt below is taken from an interview with an HCT student:

***R*** : *Did you find any patterns or relationships among the components?*

***HCT*** : *Yes.*

***R*** : *Can you explain the relationship?*

***HCT*** : *The relationship is that, to find the area of the triangle for the roof, the height isn't known — only the base. So, I used the Pythagorean theorem to find the height. Since the base is the same as the paving, the triangle's base is also the same. That's for calculating the roof area.*

***R*** : *What other relationships did you find?*

***HCT*** : *The bigger the gazebo, the more materials are needed, and the more expensive it gets. Because if the gazebo is larger, it needs more paving, and the roof follows the floor size.*

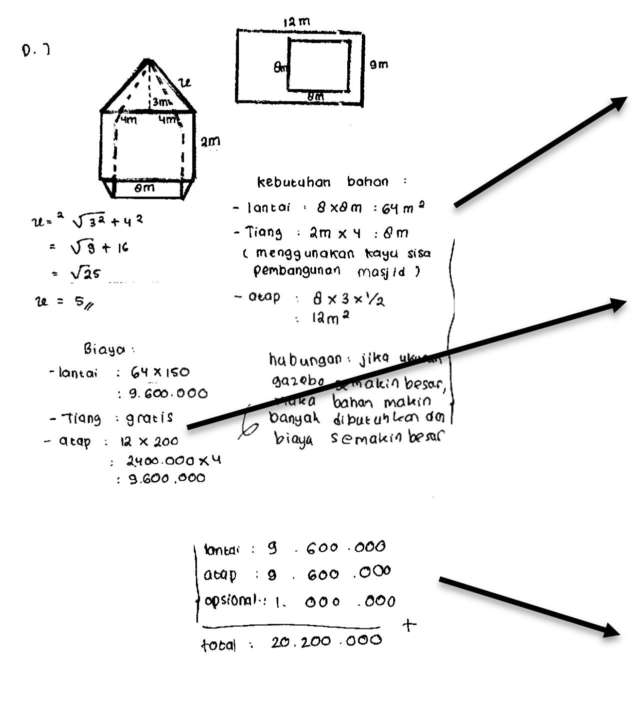
***R*** : *So, when the paving area changes, the roof also changes?*

***HCT*** : *Yes.*

***R*** : *Do you think recognising that pattern helps you solve the problem?*

***HCT*** : *Yes.*

In the Algorithmic Thinking dimension, most HCT students were able to construct a clear and structured sequence of problem-solving steps.




**Translation:**

Needed:

Flooring: $8 \times 8\,m = 64\,m^2$

Poles: $2\,m \times 4 = 8\,m$ (using wood left over from the construction of the mosque)

Roof: $8 \times 3 \times \frac{1}{2} = 12\,m^2$

Cost:

Flooring: $64 \times 150$ $(in\ thousand) = 9{,}600{,}000$

Poles: free

Roof: $12 \times 200$ $(in\ thousand) = 9{,}600{,}000$

Total:

Flooring $= 9{,}600{,}000$

Roof $= 9{,}600{,}000$

Optional $= 1{,}000{,}000$

Total $= 20{,}200{,}000$

Figure 9. HCT's answer about problem-solving steps

The excerpt below is taken from an interview with an HCT student:

**R** : *Can you explain the steps you used to solve the problem?*

**HCT** : *I started by drawing a sketch, then calculated the cost for the floor installation based on the given length and width of the field, to determine the sides of the gazebo. After that, I drew the gazebo. Then, to find the roof area, I used four triangles with the same base. Since the height wasn't given, I found it using the Pythagorean theorem. Once I got the roof area, I multiplied it by the price per square metre, then did the same for the floor, and finally summed up everything for the total cost*

4.2.2 Subjects with Medium CT Skill (MCT)

Students in the medium CT category showed varied performance across the four dimensions of Computational Thinking, with the highest average achievement in Abstraction (64%), followed by Pattern Recognition (49%), Algorithmic Thinking (46%), and Decomposition (44%). This group demonstrated developing CT skills; however, their application remained inconsistent across different problem-solving contexts.

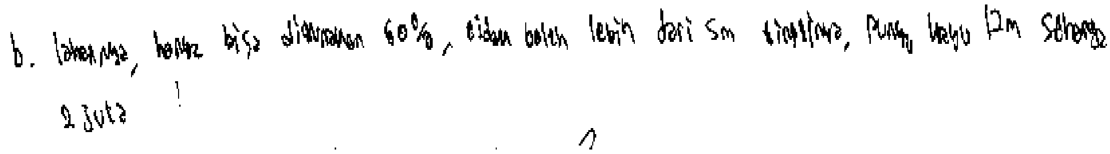
In the Decomposition dimension, some students were able to break the main problem into smaller steps and identify the basic stages, such as calculating area and cost. However, they often struggled to execute or document these steps systematically. The excerpt below is taken from an interview with an MCT student:

**R** : *Determining the budget is quite a complex problem. Did you break it into smaller parts?*

**MCT** : *Yes.*

**R** : *How did you break it down?*

**MCT** : *First, by finding the relevant information, then calculating what's needed, and determining the measurements for making the gazebo.*




**Translation:**

The land can only be used at 60% capacity, cannot exceed 5 metres in height, and has 12 metres of teak wood worth 2 million rupiah.

Figure 10. MCT's answer on identifying relevant information

In the Abstraction dimension, most students were able to identify information they considered important, but their selection process relied mainly on intuition — choosing data "used for calculation" rather than following a structured analytical process. Although they recognised that not all information was relevant, their filtering was still based on estimation and previous experience rather than deliberate reasoning.

The excerpt below is taken from an interview with an MCT student:

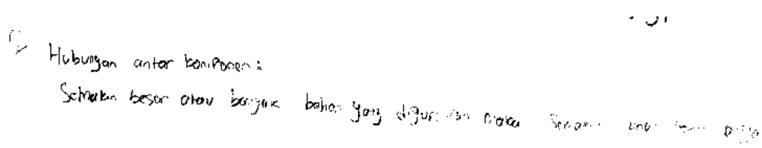
***R*** : *How did you decide which information was important and which wasn't?*

***MCT*** : *The important one is what connects to the answer or is used for calculation.*

***R*** : *So, if it's not used for calculation, it's not important?*

***MCT*** : *Yes.*

For the Pattern Recognition dimension, medium-CT students were generally able to recognise simple relationships among variables, such as between size and cost, but only after being prompted. They could identify straightforward cause-and-effect relationships but were not yet able to express them mathematically.




**Translation:**

Relationship between components:

The larger or more materials used, the higher the cost.

Figure 11. MCT's answer about the pattern recognition

The excerpt below is taken from an interview with an MCT student:

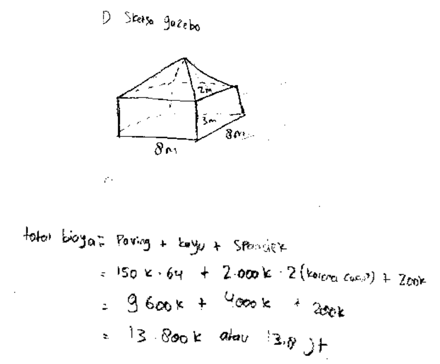
***R*** : *While solving the problem, did you find any pattern or relationship among the components?*

***MCT*** : *If the gazebo is small, the material needed is less.*

***R*** : *Did that relationship help you solve the problem?*

***MCT*** : *I'm not sure.*

In the Algorithmic Thinking dimension, most students still relied on a trial-and-error approach when determining solution steps. Only a few began to show emerging awareness of structuring their procedures in a more systematic manner.




**Translation:**

D. Gazebo Sketch

Total cost

$$
\begin{aligned}
&= floor + wood + roof \\
&= 150K \cdot 64 + 2{,}000K \cdot 2 + 200K \\
&= 9{,}600K + 4{,}000K + 200K \\
&= 13{,}800K \text{ or } 13.8M
\end{aligned}
$$

Figure 12. MCT's answer about problem-solving steps

The following is an excerpt from an interview with an MCT student:

**R** : *When solving the problem, did you try different ways directly, or did you already have a plan in mind?*

**MCT** : *I just tried it out.*

**R** : *So, you didn't have the steps planned beforehand — you figured them out as you went?*

**MCT** : *Yes, I figured it out along the way.*

4.2.3 Subjects with Low CT Skill (LCT)

Students with low CT ability demonstrated limited achievement across all four dimensions of Computational Thinking, with the lowest performance in Algorithmic Thinking (21%), followed by Pattern Recognition (32%), Abstraction (40%), and Decomposition (41%). This group exhibited unstructured reasoning patterns and tended to rely heavily on intuition when solving problems.

In the Decomposition dimension, the participants found it difficult to break the main problem into smaller sub-problems. Most proceeded directly to calculation without fully understanding the overall problem context. The excerpt below is taken from an interview with an LCT student:

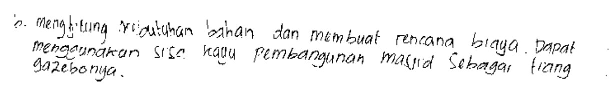
**R** : *So, you were actually asked to design and calculate the budget. Did you understand that?*

**LCT** : *I understood, but I was confused.*

**R** : *What was the first thing you did then?*

**LCT** : *I drew the sketch first, then got confused about what to do next, so I didn't write anything down.*

In the Abstraction dimension, the subjects were unable to distinguish between relevant and irrelevant information. They tended to consider all information important or were simply uncertain about how to decide which information to use.




**Translation:**

Calculate material requirements and draw up a cost plan. Leftover wood from the mosque construction can be used as gazebo poles.

Figure 13. LCT's answer on identifying relevant information

The excerpt below is taken from an interview with an LCT student:

**R** : *The problem contains a lot of information. How did you decide which one was important and which wasn't?*

**LCT** : *I was confused.*

**R** : *You were confused about deciding what's important and what's not, right?*

**LCT** : *Yes*

In the Pattern Recognition dimension, all subjects reported that they did not notice any relationships or patterns among the problem components. The excerpt below is taken from an interview with an LCT student:

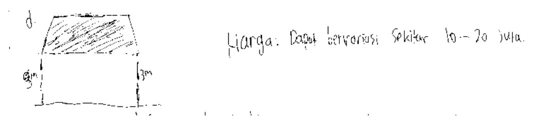
***R*** : *Did you find any similarities or relationships among the components while working on it?*

***LCT*** : *I don't think so.*

***R*** : *So, you didn't find any?*

***LCT*** : *No.*

In the Algorithmic Thinking dimension, students still relied on trial-and-error strategies without following a precise sequence of steps. They were unable to plan logical solution procedures and instead relied on estimation and prior experience.




**Translation:**

Prices: can vary between 10 and 20 million

Figure 14. LCT's answer about problem-solving steps

The excerpt below is taken from an interview with an LCT student:

***R*** : *What were your steps in solving the budgeting problem?*

***LCT*** : *I used my experience — like when I bought paint, lamps, banners, and sand before. So, I just used that kind of budget.*

***R*** : *How did you calculate it?*

***LCT*** : *Just by imagining it roughly.*

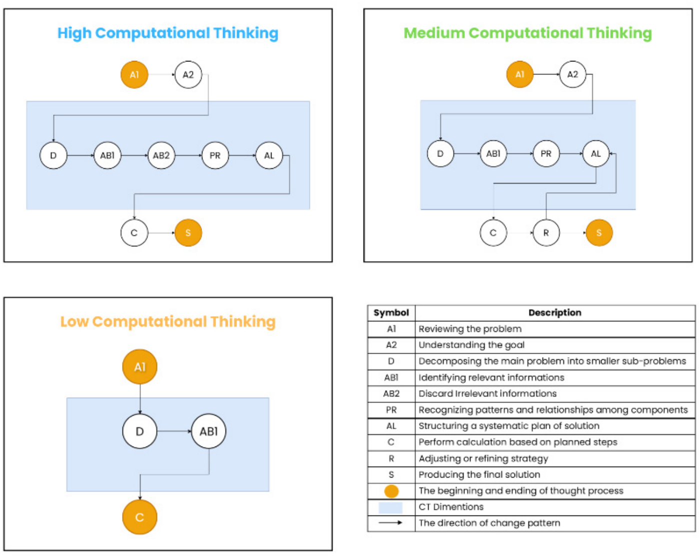
***R*** : *So, you just guessed?*

***LCT*** : *Yes.*

***R*** : *So, it was more like trial and error?*

***LCT*** : *Yes, trial and error.*

*4.3 Data Integration*




| Symbol | Description |
| --- | --- |
| A1 | Reviewing the problem |
| A2 | Understanding the goal |
| D | Decomposing the main problem into smaller sub-problems |
| AB1 | Identifying relevant informations |
| AB2 | Discard Irrelevant informations |
| PR | Recognizing patterns and relationships among components |
| AL | Structuring a systematic plan of solution |
| C | Perform calculation based on planned steps |
| R | Adjusting or refining strategy |
| S | Producing the final solution |
| | The beginning and ending of thought process |
| | CT Dimentions |
| | The direction of change pattern |

Figure 15. Computational Thinking patterns

Based on the analysis, a clear distinction was observed among the three categories of Computational Thinking (CT) ability. Students in the high CT category demonstrated systematic and logical thinking processes across all CT dimensions. They were able to comprehend complex problems holistically, select relevant information, recognise interrelated patterns, and design efficient algorithms to solve the given problems.

Students in the medium CT category exhibited developing yet inconsistent abilities. Although they were able to arrive at correct solutions, they still encountered difficulties in formulating strategies and selecting relevant information. In contrast, students in the low CT category tended to rely on intuition and trial-and-error approaches, with a limited understanding of the problem context. They struggled to identify relationships among problem components and were unable to construct systematic solution steps.

Overall, improvements across the four CT dimensions corresponded with increases in students' CPS ability. Students with high CT skills demonstrated more mature CPS performance, as they were able to analyse problems, abstract key information, and formulate structured strategies for solving complex mathematical problems.

## 5. Discussion

The findings of this study revealed that Computational Thinking (CT) had a positive and significant effect on students' Complex Problem-Solving (CPS) ability within vocational education, contributing 69.2% to the overall CPS score. This indicates that higher computational thinking abilities correspond to a greater capacity for solving complex problems. The obtained effect size suggest a strong association between CT and CPS, reflecting a meaningful educational impact. These findings reinforce Wing (2006) argument that CT is not merely a technical skill but a conceptual thinking framework that can be applied to a wide range of problems. Furthermore, the results support Shute et al. (2017) who emphasised that CT is relevant to ill-structured, real-world situations containing multiple variables, as simulated in this study.

The mixed-methods approach employed in this study enabled a deeper understanding of the relationship between CT and CPS. The quantitative results confirmed the existence of a significant effect, while the qualitative data explained the mechanisms underlying this relationship. Students with high CT ability demonstrated more systematic and logical thinking processes, whereas those with low CT ability tended to rely on unstructured, trial-and-error strategies. This pattern supports the notion that CT serves as a mode of thinking that facilitates the comprehension and resolution of complex problems (Salmon-Mordekovich, 2024).

This study examined four dimensions of CT: Decomposition, Abstraction, Pattern Recognition, and Algorithmic Thinking. The first dimension, Decomposition, refers to the ability to break down large problems into smaller, more manageable components. Wing (2006) noted that CT utilises both abstraction and decomposition to deal with large or complex problems (Min & Kim, 2020). In this study, students with high CT ability were able to decompose the main problem into smaller, manageable sub-problems, while students with low CT ability tended to struggle in breaking problems down and focused immediately on computation instead.

This study examined the influence of CT through its four dimensions. In the first dimension, Decomposition, students with high CT ability successfully decomposed the main problem into smaller, manageable sub-problems. This finding aligns with Suarsana et al. (2025) who observed that decomposition allows learners to simplify multi-layered tasks into solvable units. In contrast, low-CT students struggled to break problems down, focusing immediately on computation without a structural plan.

Regarding the second dimension, Abstraction, high-CT students demonstrated effective information selection, identifying data relevant to the solution while ignoring irrelevant contextual details. This supports the views of Richardo et al. (2025) and Kelly and Gero (2021), who posit that abstraction capabilities enable individuals to filter out noise and focus on pertinent data within complex systems. Conversely, low-CT students found it difficult to distinguish between relevant and irrelevant information, often treating all presented data as equally important.

In the Pattern Recognition dimension, high-CT students identified interconnections among variables and used these relationships to support their problem-solving processes. This reflects the process described by Wu et al. (2024) as recognising unique characteristics or regularities within a problem. Furthermore, this confirms Acosta et al. (2024) assertion that pattern recognition plays a crucial role in developing structured reasoning patterns for solving real-world problems.

Finally, in the Algorithmic Thinking dimension, high-CT students constructed clear, logical, and systematic solution sequences. This practical application reflects Lehmann (2024) definition of algorithmic thinking as a systematic reasoning process essential for procedural fluency. This systematic approach also mirrors the execution phase in Polya's problem-solving framework, ensuring accuracy in result calculation. While some medium-CT students exhibited emerging skills in this area, they lacked consistency. In contrast, low-CT students relied on intuition and calculation without prior planning, resulting in suboptimal solutions

The findings of this study carry important implications for vocational education, particularly in addressing the skill gap in complex problem-solving that contributes to the high unemployment rate among vocational graduates. Although Informatics Engineering students are generally more exposed to CT-related concepts through programming logic and technology-assisted learning (Hsu, 2025; Lee et al., 2022), the results indicate that mere exposure to technology does not necessarily ensure the development of effective computational thinking skills. Therefore, CT principles should be explicitly integrated across various subjects—particularly mathematics—to cultivate logical and systematic thinking skills that directly enhance students' CPS ability. As Araya et al. (2021) emphasised, CT can be developed through learning activities in every subject across the curriculum, not limited to computer science, but as a fundamental cognitive approach that supports problem-solving in diverse contexts.

Despite the strong relationship found between CT and CPS, several limitations must be acknowledged. This study focused on a single vocational major, limiting the generalisability of findings to other fields. Additionally, the usage of self-developed instruments, though validated, may introduce potential measurement bias. Future studies should employ standardised CT and CPS instruments and expand the participant base across different vocational programmes. Moreover, longitudinal studies could be conducted to track the development of CT and CPS over time, from schooling to the workplace, to provide a more comprehensive understanding of how CT contributes to shaping 21st-century competencies in vocational education.

## 6. Conclusions

This study demonstrated that CT has a positive and significant effect on the CPS ability of vocational high school students majoring in Informatics Engineering. The findings confirmed that the higher the students' CT ability, the better their capacity to solve complex mathematical problems. Qualitative analysis further reinforced this result, showing that students with high CT ability were able to decompose problems into smaller, manageable sub-problems (decomposition), identify relevant information (abstraction), recognise relationships between variables (pattern recognition), and construct systematic solution steps (algorithmic thinking). In contrast, students with medium CT ability exhibited logical thinking but lacked consistency in applying strategies, while those with low CT ability relied more on intuition and trial-and-error approaches.

Theoretically, these findings support the view that CT functions as a conceptual framework that enables individuals to address complex problems systematically and logically. In practice, the study suggests that teaching practices in vocational schools should explicitly integrate CT principles across subjects, including mathematics, to develop structured thinking and problem-solving skills aligned with the demands of the modern workforce. Hence, CT should not be viewed merely as a technical skill in programming but as a universal cognitive competence that enhances employability and fosters 21st-century skills among vocational students.

**Acknowledgments**

The author would like to express sincere gratitude to SMKN 1 Magelang and SMKN 2 Temanggung for their permission, support, and facilities provided during the conduct of this research. Special thanks are also extended to the research instrument validators, who generously dedicated their time and provided valuable feedback for the refinement of the Computational Thinking and Complex Problem-Solving instruments.

**Authors contributions**

Muhammad Irvan Ardianto was responsible for conceptualization, data collection, data analysis, and writing the original draft. Megita Dwi Pamungkas and Nina Agustyaningrum provided supervision and contributed to reviewing and revising the manuscript. All authors read and approved the final manuscript.

**Funding**

Not Applicable.

**Competing interests**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Informed consent**

Obtained.

**Ethics approval**

The Publication Ethics Committee of the Redfame Publishing.

The journal's policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

**Provenance and peer review**

Not commissioned; externally double-blind peer reviewed.

**Data availability statement**

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

**Data sharing statement**

No additional data are available.

**Open access**



**Copyrights**



**References**

Acosta, Y., Alsina, Á., & Pincheira, N. (2024). Computational thinking and repetition patterns in early childhood education: Longitudinal analysis of representation and justification. *Education and Information Technologies*, *29*(6), 7633-7658. https://doi.org/10.1007/s10639-023-12051-6

Aiken, L. R. (1985). Three coefficients for analyzing the reliability and validity of ratings. *Educational and Psychological Measurement*, *45*, 131・142. https://doi.org/10.1177/0013164485451012

Altan, B. A., & Altıntas, H. O. (2017). Professional identities of vocational high school students and extracurricular activities. *Journal of Education and Training Studies*, *5*(7), 46. https://doi.org/10.11114/jets.v5i7.2446

Aminah, N., Sukestiyarno, Y. L., Cahyono, A. N., & Maat, S. M. (2023). Student activities in solving mathematics problems with a computational thinking using Scratch. *International Journal of Evaluation and Research in Education*, *12*(2), 613-621. https://doi.org/10.11591/ijere.v12i2.23308

Anggraini, R. D., Pratowo, T., & Sudibyo, E. (2022). Analysis of problem solving skills in the vocational high school using direct current electricity as a case study. *IJORER : International Journal of Recent Educational Research*, *3*(3), 301-311. https://doi.org/10.46245/ijorer.v3i3.219

Araya, R., Isoda, M., & Moris, J. van der M. (2021). Developing computational thinking teaching strategies to model pandemics and containment measures. *International Journal of Environmental Research and Public Health*, *18*(23). https://doi.org/10.3390/ijerph182312520

Arfé, B., Vardanega, T., & Ronconi, L. (2020). The effects of coding on children's planning and inhibition skills. *Computers & Education*, *148*, 103807. https://doi.org/10.1016/j.compedu.2020.103807

Bouck, E. C., Sands, P., Long, H., & Yadav, A. (2021). Preparing special education preservice teachers to teach computational thinking and computer science in mathematics. *Teacher Education and Special Education*, *44*(3), 221-238. https://doi.org/10.1177/0888406421992376

Celik, I. (2023). Exploring the determinants of artificial intelligence (ai) literacy: digital divide, computational thinking, cognitive absorption. *Telematics and Informatics*, *83*(102026), 1-11. https://doi.org/10.1016/j.tele.2023.102026

Çetin, N. M. (2025). A comparison of the programming-oriented computational thinking skills of engineering and nonengineering students at turkish universities. *Computer Applications in Engineering Education*, *33*(5). https://doi.org/10.1002/cae.70069

Creswell, J. W., & Creswell, J. D. (2018). *Research Design: qualitative, quantitative, and mixed methods approaches* (5th ed.). Los Angles: SAGE Publications, Inc.

Dehbozorgi, N., & Roopaei, M. (2024). Improving computational thinking competencies in stem higher education. *2024 IEEE Integrated STEM Education Conference (ISEC)*, 01-04. IEEE. https://doi.org/10.1109/ISEC61299.2024.10664997

Denning, P. J., & Tedre, M. (2021). Computational Thinking: a disciplinary perspective. *Informatics in Education*, *20*(3), 361-390. https://doi.org/10.15388/infedu.2021.21

Fei, J., Dong, S., & Fei, D. (2025). Computational thinking in complex problem solving based on data analysis: exploring the role of problem representation using the Tower of Hanoi. *Advances in Continuous and Discrete Models*, *2025*(1). https://doi.org/10.1186/s13662-025-03866-3

Frisnoiry, S., Sihotang, H. M. W., Indri, N., & Munthe, T. (2024). Analysis of unemployment issues in Indonesia. *Jurnal Ilmiah Komputerisasi Akutansi*, *17*(1), 365-374. https://doi.org/10.51903/kompak.v17i1.1866

Funke, J. (2012). Complex problem solving. In N. M. Seel (Ed.), *Encyclopedia of the Sciences of Learning* (Vol. 38, pp. 682-685). Heidelberg: Springer. https://doi.org/10.1007/978-1-4419-1428-6_685

Funke, J. (2019). Problem solving. In R. J. Strenberg & J. Funke (Eds.), *The Psychology of Human Thought* (pp. 167-168). Heidelberg: Heidelberg University Publishing.

Funke, J. (2021). It requires more than intelligence to solve consequential world problems. *Journal of Intelligence*, Vol. 9. MDPI AG. https://doi.org/10.3390/jintelligence9030038

Greiff, S., Stadler, M., Sonnleitner, P., Wolff, C., & Martin, R. (2015). Sometimes less is more: Comparing the validity of complex problem solving measures. *Intelligence*, *50*, 100-113. https://doi.org/10.1016/j.intell.2015.02.007

Guilford, J. P. (1956). *Fundamental statistics in psychology and education*. New York: Mc Graw-Hill Book Co. Inc.

Hegde, S. N., & Kavade, M. P. (2025). Bridging skill gap: a study on industry expectations vs. Graduate competencies. *International Journal for Multidisciplinary Research*, *7*(3), 1-6. https://doi.org/10.36948/ijfmr.2025.v07i03.44225

Helsa, Y., Juandi, D., & Turmudi. (2023). Computational thinking skills indicators in number patterns. *Mathematics Education Journal*, *17*(2), 167-188. https://doi.org/10.22342/jpm.17.2.20042.167-188

Hsu, H. P. (2025). From Programming to Prompting: developing computational thinking through large language model-based generative artificial intelligence. *TechTrends*, *69*(3), 485-506. https://doi.org/10.1007/s11528-025-01052-6

Huang, W., & Looi, C. K. (2021). A critical review of literature on “unplugged” pedagogies in K-12 computer science and computational thinking education. *Computer Science Education*, *31*(1), 83-111. https://doi.org/10.1080/08993408.2020.1789411

Kelly, N., & Gero, J. S. (2021). Design thinking and computational thinking: A dual process model for addressing design problems. *Design Science*, *7*, 1-5. https://doi.org/10.1017/dsj.2021.7

Lee, S. J., Francom, G. M., & Nuatomue, J. (2022). Computer science education and K-12 students’ computational thinking: A systematic review. *International Journal of Educational Research*, *114*(102008). https://doi.org/10.1016/j.ijer.2022.102008

Lehmann, T. H. (2024). How current perspectives on algorithmic thinking can be applied to students’ engagement in algorithmatizing tasks. *Mathematics Education Research Journal*, *36*(3), 609-643. https://doi.org/10.1007/s13394-023-00462-0

Lehmann, T. H. (2025). Examining the interaction of computational thinking skills and heuristics in mathematical problem solving. *Research in Mathematics Education*, *27*(2), 269-290. https://doi.org/10.1080/14794802.2025.2460460

Mailisman, N., Ikhsan, M., & Hajidin. (2020). Mathematics problem-solving skills of vocational high school students related to the 21st-century education. *Journal of Physics: Conference Series*, *1460*(1). Institute of Physics Publishing. https://doi.org/10.1088/1742-6596/1460/1/012014

Min, S. H., & Kim, M. K. (2020). Developing children’s computational thinking through physical computing lessons. *International Electronic Journal of Elementary Education*, *13*(2), 183-198. https://doi.org/10.26822/iejee.2021.183

Molnár, G., & Greiff, S. (2023). Understanding transitions in complex problem-solving: Why we succeed and where we fail. *Thinking Skills and Creativity*, *50*. https://doi.org/10.1016/j.tsc.2023.101408

Montuori, C., Gambarota, F., Altoé, G., & Arfé, B. (2024). The cognitive effects of computational thinking: A systematic review and meta-analytic study. *Computers and Education*, *210*. https://doi.org/10.1016/j.compedu.2023.104961

Nyström, S., & Ahn, S. E. (2025). Vocational students’ experiences and reflections on simulation training–what differences enable or hinder learning? *Journal of Vocational Education and Training*. https://doi.org/10.1080/13636820.2025.2449659

OECD. (2014). *PISA 2012 results: creative problem solving (Volume V)*. OECD. https://doi.org/10.1787/9789264208070-en

Pamungkas, M. D., Waluya, S. B., & Mariani, S. (2023). A systematic review of complex problem-solving in education and mathematics education. *Journal of Higher Education Theory and Practice*, *23*(16), 87-101. https://doi.org/10.33423/jhetp.v23i16.6465

Pirzado, F. A., Ahmed, A., Hussain, S., Ibarra-Vázquez, G., & Terashima-Marin, H. (2025). Assessing computational thinking in engineering and computer science students: a multi-method approach. *Education Sciences*, *15*(3). https://doi.org/10.3390/educsci15030344

Polya, G. (1945). *How to solve it: a new aspect of mathematical method*. Princeton: Princeton University Press.

Richardo, R., Dwiningrum, S. I. A., Murti, R. C., Wijaya, A., Adawiya, R., Ihwani, I. L., … & Aryani, A. E. (2025). Computational thinking skills profile in solving mathematical problems based on computational thinking attitude. *Journal of Education and Learning*, *19*(2), 1157-1166. https://doi.org/10.11591/edulearn.v19i2.21643

Salmon-Mordekovich, N. (2024). Success starts with the first step: insight problem-solving stages and their underlying cognitive strategies. *Journal of Cognitive Psychology*, *36*(4), 523-534. https://doi.org/10.1080/20445911.2024.2356288

Salwadila, T., & Hapizah. (2024). Computational thinking ability in mathematics learning of exponents in grade ix. *Infinity Journal*, *13*(2), 441-456. https://doi.org/10.22460/infinity.v13i2.p441-456

Shute, V. J., Sun, C., & Asbell-Clarke, J. (2017). Demystifying computational thinking. *Educational Research Review*, *22*, 142-158. Elsevier Ltd. https://doi.org/10.1016/j.edurev.2017.09.003

Statistics Indonesia. (2024). Open unemployment rate based on education level, 2024. Retrieved May 8, 2025, from https://www.bps.go.id/id/statistics-table/2/MTE3OSMy/tingkat-pengangguran-terbuka-berdasarkan-tingkat-pendidikan.html

Suarsana, I. M., Jupri, A., Suryadi, D., Nurlaelah, E., Nyoman, G., & Hartawan, Y. (2025). An analysis of mathematics teaching and learning process to enhance computational thinking: the case of straight-line equations. *Mathematics Teaching Research Journal*, *17*(2).

Sukkamart, A., Sermsri, N., Kantathanawat, T., Nakwijit, R., & Meekhobtong, S. (2024). Computer education student teacher complex problem-solving skills development using computational thinking and visualization tools. *Pakistan Journal of Life and Social Sciences*, *22*(2), 4915-4923. https://doi.org/10.57239/PJLSS-2024-22.2.00364

Tomperi, P. (2020). Evaluation of the secondary students' attitudes towards studying and learning science and mathematics, and their impact on learning in the two schools in the northern finland. *Journal of Education and Training Studies*, *8*(12), 16. https://doi.org/10.11114/jets.v8i12.5080

Wahab, N. A., Talib, O., Razali, F., & Kamarudin, N. (2021). The big why of implementing computational thinking in stem education: a systematic literature review. *Malaysian Journal of Social Sciences and Humanities (MJSSH)*, *6*(3), 272-289. https://doi.org/10.47405/mjssh.v6i3.706

Wing, J. M. (2006). Computational thinking. *Communications of the ACM*, *49*(3), 33-35. https://doi.org/10.1145/1118178.1118215

Wing, J. M. (2008). Computational thinking and thinking about computing. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *366*(1881), 3717-3725. https://doi.org/10.1098/rsta.2008.0118

World Economic Forum. (2020). These are the top 10 job skills of tomorrow – and how long it takes to learn them. Retrieved May 9, 2025, from https://www.weforum.org/stories/2020/10/top-10-work-skills-of-tomorrow-how-long-it-takes-to-learn-them/

Wu, T. T., Asmara, A., Huang, Y. M., & Permata Hapsari, I. (2024). Identification of problem-solving techniques in computational thinking studies: Systematic Literature Review. *International Journal of STEM Education*, *14*(2), 1-20. https://doi.org/10.1177/21582440241249897

Yadav, A., Ocak, C., & Oliver, A. (2022). Computational thinking and metacognition. *TechTrends*, *66*(3), 405-411. https://doi.org/10.1007/s11528-022-00695-z

Yeni, S., Nijenhuis-Voogt, J., Saeli, M., Barendsen, E., & Hermans, F. (2024). Computational thinking integrated in school subjects – A cross-case analysis of students' experiences. *International Journal of Child-Computer Interaction*, *42*. https://doi.org/10.1016/j.ijcci.2024.100696

Yustiana, Y., Kusmayadi, T. A., & Fitriana, L. (2021). Mathematical problem solving ability of vocational high school students based on adversity quotient. *Journal of Physics: Conference Series*, *1806*(1). IOP Publishing Ltd. https://doi.org/10.1088/1742-6596/1806/1/012092