

## Computational Thinking Skill Profile of Prospective Science Teacher Students in the Dynamic Electricity

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### Article Info

#### Keywords:

computational thinking skills  
science teacher candidates  
dynamic electricity

#### Article History:

Received: February 14, 2025

Accepted: September 22, 2025

Publish: September 29, 2025

#### DOI:

10.33830/jp.v26i2.10282.2025

### Abstract

This study aims to describe the Computational Thinking Skill (CTS) profile of prospective science teacher students in solving problems with dynamic electricity material. This study uses a descriptive method with a quantitative approach. The data collection technique in this study used a CTS essay test of 10 questions and a multiple-choice computational thinking test, which were then analyzed using quantitative descriptive analysis. Based on the results of the study, it is known that the level of CTS ability of prospective science teacher students is 43.74% so it is categorized as sufficient. The highest level that students can achieve is 53.15%, which is an indicator of pattern recognition ability, and the lowest level is 32.28%, which indicates abstraction ability. Meanwhile for other indicators, namely algorithms and decomposition, the results obtained were 40.34% and 49.19% respectively.

## INTRODUCTION

Technological development is occurring rapidly, marked by the presence of computing in various aspects of life, as well as artificial intelligence and the internet of things as the foundation for human-machine interaction (Munawarah et al., 2021). The influx of computing into various areas of life offers several advantages and conveniences for humanity, thus presenting new challenges for the education sector: preparing students for this computing era (Hussin, 2018; Lase, 2019). One step that can be taken to address future challenges is to design learning that enhances computational thinking skills.

Although CT was considered a skill only possessed by computer scientists for many years, Wing (2006) defines it as a skill that everyone should have. CT is like basic reading, writing, and math skills, so everyone should have them. Hsu et al. (2018) consider CT as a universal skill that should be integrated into everyday life. Most researchers agree that CT is a 21st-century skill that must be possessed by students at all levels of education from preschool to higher education.

Computational thinking is critical to develop because it is a means to develop problem-solving skills and student creativity integrated with technological developments (NRC, 2011). Computational thinking is considered a fundamental skill for today's world because computational thinking ability is known as a basic cognitive problem-solving procedure that

facilitates solving everyday problems (Harangus & Káta, 2020; Kalelioğlu et al., 2016).

Computational thinking is crucial given that educational institutions must be brought closer to the employment context from a global perspective. Computational thinking skills are not exclusive to computer scientists but are fundamental for everyone. In accordance with the opinion of (Denning, 2009; Denning & Tedre, 2019) the computational methods that emerged were initially intended to support the development, trade, and research sectors across various disciplines. This is because the process of thinking using computers involves problem-solving steps that can be applied in many areas of life. This thinking process involves reflecting on seemingly complex problems into ones we know how to solve, whether by subtracting, adding, transforming, or simulating. According to Wing (2006), Computational thinking does not mean thinking like a computer but rather engaging in five cognitive processes to solve problems efficiently and creatively.

From the explanation above, it is essential for everyone, including prospective science teacher students, to master computational thinking skills. One way to facilitate this ability is first to find out the students' computational thinking profile, which is measured through a computational test instrument in science learning. The test instrument was integrated with science learning content to obtain data on computational thinking skills in science. Dynamic electricity material is one of the science materials related to computing, so it is relevant to use to determine student profiles. Based on this, this study aims to describe the profile of prospective science teacher students' computational thinking skills on dynamic electricity material to support a well-planned learning process that leads to the development of computational thinking skills.

## RESEARCH METHODS

A quantitative approach was used in this research. The descriptive approach describes phenomena that occur in a real, realistic, and actual way and explains the relationships between the phenomena being investigated (Rukajat, 2018). This is because a quantitative approach is used in data collection, interpretation, and research results (Jayusman & Shavab, 2020). The population in this study was all prospective science teacher students at a State University in Yogyakarta for the 2023/2024 academic year. The sample used was fourth-semester students in classes A and B, with 34 students each taking the Electricity and Magnetism course.

The materials used in this computational thinking skills test include experiments on Ohm's law, specific resistance, the effect of temperature on resistance, resistors and voltage sources, charge and Coulomb force, electrons and electric fields, the relationship between charge and electric potential difference, and capacitor circuits. The lecturer conducted the lesson without any special treatment to achieve computational thinking skills.

Students were tested with written computational thinking skills questions accompanied by answer sheets containing instructions to help them solve the questions. The test consisted of 10 essay questions on computational thinking skills, algorithmic thinking, and 20 multiple-choice questions covering aspects of decomposition, pattern recognition, and abstraction. The instrument was validated through content validation involving five experts. Data were analyzed using the Content Validity Ratio (CVR) with the following equation.

$$CVR = \frac{\left(\frac{n_e - \frac{N}{2}}{\frac{N}{2}}\right)}{\frac{N}{2}} \quad (1)$$

**Table 1.** The results of the Analysis

No.	Item	Expert					V Aiken	Result
		Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
1	A1	3	4	4	3	3	0.99	Valid
2	A2	4	4	3	3	4	0.99	Valid
3	A3	4	4	4	4	4	0.99	Valid
4	B1	3	4	4	3	3	0.99	Valid
5	B2	3	4	4	3	3	0.99	Valid
6	B3	3	4	4	3	3	0.99	Valid
7	C1	4	4	3	3	4	0.99	Valid
8	C2	4	4	4	4	4	0.99	Valid
9	C3	3	4	4	3	3	0.99	Valid
10	D1	3	4	4	3	3	0.99	Valid
11	D2	3	4	4	3	3	0.99	Valid
12	D3	4	4	3	3	4	0.99	Valid
13	E1	4	4	4	4	4	0.99	Valid
14	E2	3	4	4	3	3	0.99	Valid
15	E3	3	4	4	3	3	0.99	Valid
16	F1	3	4	4	3	3	0.99	Valid
17	F2	4	4	3	3	4	0.99	Valid
18	F3	4	4	4	4	4	0.99	Valid
19	G1	3	4	4	3	3	0.99	Valid
20	G2	3	4	4	3	3	0.99	Valid
21	G3	3	4	4	3	3	0.99	Valid
22	H1	4	4	3	3	4	0.99	Valid
23	H2	4	4	4	4	4	0.99	Valid
24	H3	3	4	4	3	3	0.99	Valid
25	I1	3	4	4	3	3	0.99	Valid
26	I2	3	4	4	3	3	0.99	Valid
27	I3	4	4	3	3	4	0.99	Valid
28	J1	4	4	4	4	4	0.99	Valid
29	J2	3	4	4	3	3	0.99	Valid
30	J3	3	4	4	3	3	0.99	Valid

The results of the computational thinking skills test were scored, assessed, analyzed using quantitative descriptive analysis techniques, and categorized according to the provisions in [Table 1 \(Khairani et al., 2021\)](#).

**Table 2.** Percentage Qualification of Computational Thinking Skill

No	Percentage	Category
1	81% – 100%	Very Good
2	61% – 80,99%	Good
3	41% – 60,99%	Sufficient
4	21% – 40,99%	Low
5	0% – 20,99%	Very Low

## RESULTS AND DISCUSSION

The data for this study were obtained from responses to written tests measuring computational thinking skills. These responses were evaluated based on students' problem-

solving abilities and assessed using specific indicators. The analysis aimed to determine the extent of students' computational thinking skills. The results of the test are presented in [Table 3](#).

**Table 3.** Test Result of Computational Thinking Skill

Data Component	Number of Students	Minimum Score	Maximum Score	Mean	Std. Dev.
Student in the 4 <sup>th</sup> semester	74	20.9	62,7	41,448	10,312

The sum of the scores from each test was used to calculate the total test score. [Table 3](#) shows the levels of students' computational thinking achievement, divided into several categories. The average score indicates that the computational thinking level of prospective science teachers was 41.45%, indicating a sufficient level.

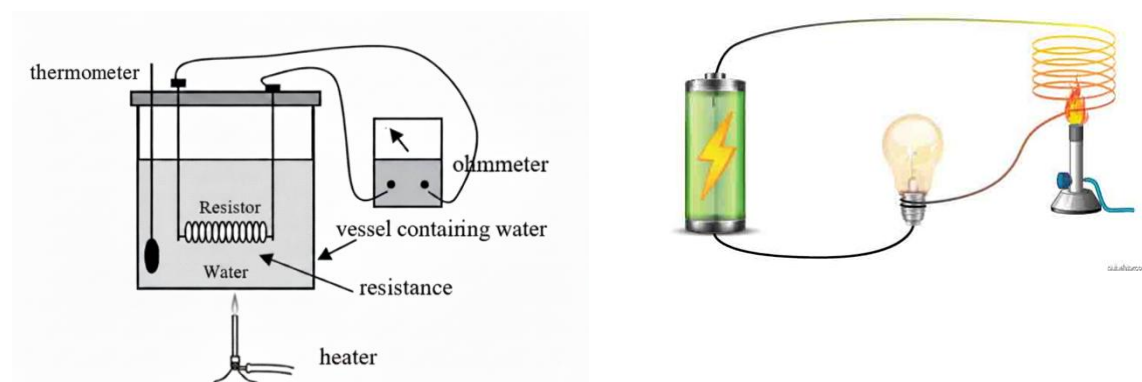
[Table 4](#) shows the percentages for each computational thinking indicator. The percentage values were obtained by combining the average score for each indicator with the total score for that indicator and then converting them into percentages. The highest score for the mathematical thinking level category reached only half of the maximum possible score.

**Table 4.** Percentage of Each Computational Thinking Indicator

Computational Thinking Aspect	Score	Category
Abstraction	32,28%	Low
Algorithm	40,34%	Low
Decomposition	49,19%	Low
Pattern Recognition	53,15%	Sufficient

Computational Thinking (CT) is basically a student's thinking activity in understanding the context of the problem, then the student will reason up to the abstraction stage and end up with a systematic problem solving ([Cahdriyana, 2020](#); [Zydney et al., 2020](#)). This low level of computational thinking ability is reflected in the students' suboptimal responses to the questions on electricity and magnetism. A more detailed explanation of each computational thinking indicator in the electricity and magnetism material is as follows.

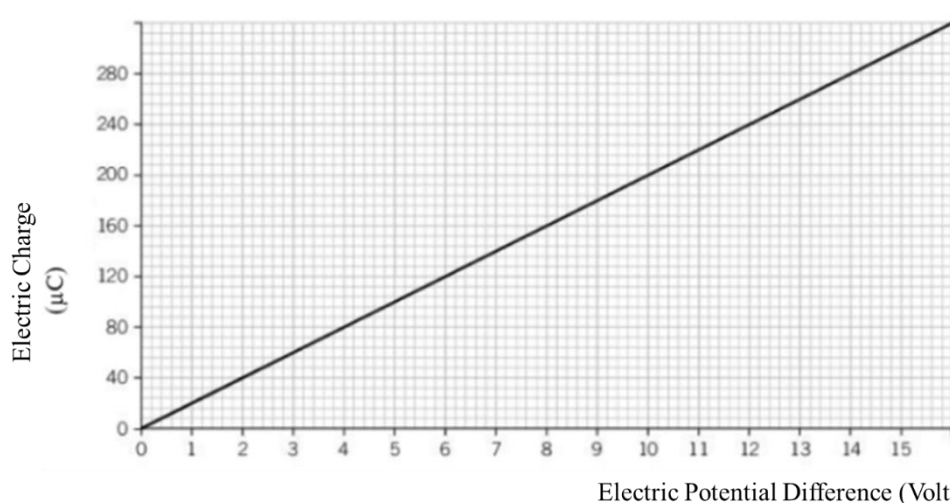
**Decomposition Indicator.** Decomposition is a Computational Thinking indicator whose score is still categorized as low. The decomposition indicator is captured through a test on electromagnetism material that divides a problem into several smaller sub-problems. In this case, one example is students being asked to decompose the experimental variables (smaller sub-problems) from the main experimental design related to "proving the effect of temperature on resistance."



**Figure 1.** Experimental design "proving the effect of temperature on resistance"

Students are asked to answer the question "Based on the image above, it can be concluded that the experimental variables in the experimental design include which of the following?". In this example, students should provide the answer "Independent variable: temperature; Dependent variable: resistance value, and Control variable: resistor material". Many students have not been able to break down problems into their constituent subproblems, so students' decomposition abilities are still low. According to [Pollock et al \(2019\)](#). Decomposition is the ability to break down problems into their constituent subproblems.

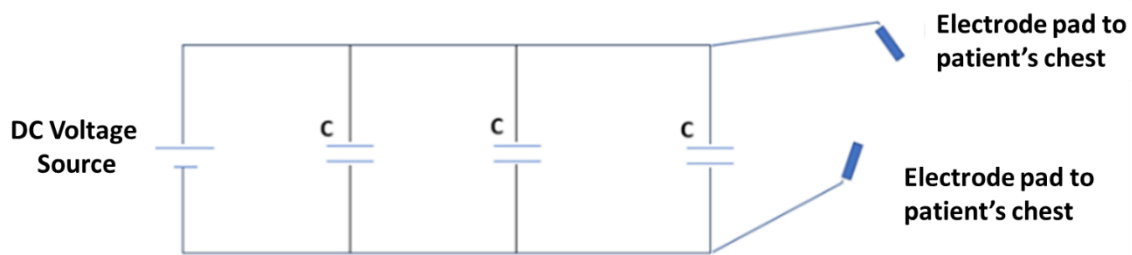
Pattern Recognition Indicator. Pattern recognition is the observation or analysis of similarities between problems. A person is expected to find patterns in similar problems and patterns in solutions designed/implemented after repeatedly solving the problem. In this case, one example is a student is asked to observe the graph of the relationship between the amount of charge  $Q$  ( $\mu\text{C}$ ) and the electrical potential difference  $V$  (Volts) across a capacitor. In the test, an experimental design image is presented as [Figure 2](#).



**Figure 2.** Relationship between charge and electric potential difference

Students are asked to answer the following questions: "The charge stored in a capacitor is...." In this example, students should answer "Directly proportional to the potential difference." In this case, some students could identify the pattern and provide the correct answer. Recognizing this pattern requires analyzing known data. According to [Danindra & Masriyah \(2020\)](#), the general formula for solving problems is obtained from previously known patterns.

Abstraction is the process of eliminating irrelevant parts of a problem. Abstraction allows you to create a blueprint for solving a problem that can be used to solve similar problems. In this case, one example is that students are asked to analyze a question about "an electrical circuit using several resistors and a voltage source." In this example, students should answer "wrong" for the statement "The sum of the voltages in loop 1 and loop 2 is zero because it is an open circuit" and answer "true" for the statement "The circuit is a direct current circuit because the voltage source with the symbol  $\text{---}\text{||}\text{---}$ ". Many students fail to answer the irrelevant questions correctly. They do not understand the problem and therefore cannot eliminate irrelevant parts. This is in accordance with the findings of [Fitry \(2022\)](#) who found that the biggest mistake in understanding a problem is writing down what is known and what is asked in the question.



**Figure 3.** Capacitor design and capacitance value

An algorithm is a sequence of steps to solve a problem. Algorithms must be clearly structured, coherent, complete, efficient, and adhere to the problem's limitations. In this case, one example is a student being asked to design a capacitor circuit to measure the capacitance value of a capacitor. Capacitance energy can be used as a stimulator to restore the heart to normal function when symptoms of ventricular fibrillation occur. In this example, the student should provide the following answer.

Many students are unable to answer sequentially. Their answers are unclear, incoherent, and incomplete. Some answers are out of context or beyond the boundaries of the problem, resulting in different algorithms being generated when other people try the same problem. [Wing \(2017\)](#) defines computational thinking as the ability to present problems and solutions using specific algorithms, enabling other people and computers to solve the same problem.

Computational thinking scores among prospective science teachers are moderate and low, particularly in the topic of Electricity and Magnetism. This is a problem that requires improvement. According to research by [Ni'am et al. \(2022\)](#), low computational thinking is due to various factors, including general learning and a lack of innovative learning design in lesson planning.

In another study conducted by [Nursya'baani et al. \(2022\)](#), it was found that students' inability to meet learning objectives and apply the learning elements used can contribute to low levels of cognitive computing abilities. In addition, it was found that teaching materials, media, learning methods, and analysis of students' additional needs are just some of the supporting components of learning that can impact students' levels of cognitive computing abilities. In addition, other common factors that cause students to score low in completing a Computational Thinking problem are time and accuracy. According to [Amalia \(2017\)](#), one of the students' mistakes in solving problems is confusion in determining the steps to solve the problem and running out of time in solving the problem. In addition, many students are also rushed and less careful in writing the information asked in the question ([Nurussafa'at et.al, 2016](#)).

## CONCLUSION

Based on the average score, it is known that the computational thinking level of prospective science teachers is 41.448%, so it is categorized as sufficient. When viewed from each indicator, it is known that only the pattern recognition indicator is categorized as sufficient (53.15%). In contrast, the other indicators, namely abstraction, are categorized as low (32.28%), algorithmic thinking is categorized as low (40.34%), and decomposition is categorized as low (49.19%).



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