



## Computational Thinking Skill of Prospective Mathematics Teachers in Statistic Methods Courses

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DOI: <http://dx.doi.org/10.18592/tarbiyah.v14i1.14559>

<b>Key Words:</b> computational thinking mathematics education prospective mathematics statistics	<b>Abstract:</b> The statistics methods course is compulsory in the Mathematics Study Program, which uses applications according to technological developments, including the SPSS application. This study describes the computational Thinking of prospective mathematics teachers in solving statistics problems in statistics methods courses. This research is quantitative-qualitative descriptive research. The subjects were 88 students in the statistics methods course in the 2022/2023 academic year. The research instrument was a test containing three statistics problems. The findings have indicated that the computational Thinking of prospective mathematics teachers in solving statistics problems was in the Very Good Category with a percentage of 2,27%, the Good Category was 31,8%, the Enough category was 38,64%, the low Category was 19,32%, and the deficient Category was 7,95%. The researchers suggest that ongoing research needs to be conducted to improve students' computational thinking skills, and it is necessary to look for factors that influence students' computational thinking skills.
<b>Received</b> : 19 November 2024 <b>Revised</b> : 5 May 2025 <b>Accepted</b> : 5 May 2025 <b>Published</b> : 21 May 2025	

**To cite this article:** Juhairiah, Ansori., H., Amalia., R. (2025). Computational Thinking Skill of Prospective Mathematics Teachers in Statistic Methods Courses . *Tarbiyah: Jurnal Ilmiah Kependidikan*. 14 (1), 85-96.

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## Introduction

Sustainable Development Goals (SDGs) are a series of global goals or commitments set by the United Nations at the General Assembly in September 2015. There are 17 interrelated and supporting goals used to overcome various global challenges humans face, including eradicating poverty, ensuring education and gender equality, reducing economic inequalities, promoting sustainable development, and protecting the environment (United Nation, 2015). Computational thinking is one of the pillars that supports the Sustainable Development of Individuals and the digital world (He et al., 2021). This is also supported by a study that shows that computational thinking and its sub-competencies, including decomposition, pattern recognition, abstraction, and algorithms, have a significant role in promoting sustainable development and advancing the SDGs, specifically SDG 4 (quality education), SDG 5 (gender equality), SDG 6 (clean water and sanitation), and SDG 11 (sustainable cities and communities). So, it can be said that Computational thinking can play a significant role in advancing the Sustainable Development Goals (SDGs), especially by providing structured approaches to problem-solving that can be applied to various global challenges (Voogt et al., 2015; Bocconi et al., 2018; Ramírez-Montoya et al., 2023).

Computational thinking, as introduced by Seymour Papert and Jeannette M. Wing (Lodi & Martini, 2021), was defined as a way of thinking that uses fundamental ideas from computer science to addressvoogts issues, design systems, and understand human behavior (Wing, 2006). Wing (2006) states that computational thinking is a skill that is not only useful for computer scientists but is also a fundamental skill that a person must learn, such as reading, writing, and arithmetic. Based on this, it is concluded that computational thinking is one of the essential skills a person must have in the 21st century when computers and technology are part of life.

In the field of education, especially education and mathematics learning. Computational thinking has been studied and concluded to be an important skill closely related to mathematics. This is because students will use their thinking skills to solve problems with regular work patterns and calculations (Chan et al., 2020). Several other studies regarding computational thinking and mathematics education show that computational thinking and mathematical habits of mind are interconnected with instruction (Pei et al., 2018). Then, computational thinking is closely related to mathematical thinking, especially in solving mathematical problems with an analytical construction process in solving problems (Islami et al., 2023). Apart from that, good Computational Thinking Skills support high-level abilities, according to Tim Penyusun Materi ITB (Fauzi et al., 2024).

Seeing the importance of computational thinking skills as described above, a prospective mathematics teacher has a role in developing the 21st century. If an educator uses his computational thinking skill in learning, a process of identifying patterns occurs, solving complex problems into small parts (Lestari et al., 2020; Rijal Kamil et al., 2021; Simanjuntak et al., 16935), organizing and making plans to find solutions and be able to represent the data (Kalelioglu et al., 2016; Rahmadhani & Mariani, 2021; Rijal Kamil et al., 2021).

Students studying in the Mathematics Education study program at Lambung Mangkurat University must be equipped with mathematical abilities, one of which is good Computational Thinking Skills. So that students whose prospective mathematics

teachers can make decisions and solve problems (Sundendar et al., 2020). Statistics is one of the sciences studied by prospective mathematics teachers. Statistics is a science used in all fields, used to collect, organize, present, and analyze data, draw valid conclusions, and make appropriate decisions based on the analysis carried out (Tayeb et al., 2014). Statistics is studied in the statistical methods course. The Statistical Methods course is compulsory, with three credits in the 4th semester. In the statistical methods course, prospective mathematics teachers learn about matters related to statistics, which include the meaning of statistics, types of data, data presentation, measures of data centralization, measures of sharpness, graphs/curves, random variables, and continuous random variables, normal distribution, data distribution, testing two independent and paired samples, ANOVA, mean difference test (t-test), correlation test, regression test, accompanied by an introduction to and use of the SPSS program for each statistical test.

They can obtain either through problems around the students, either through direct observation or undirect via the internet. Using the SPSS application as a tool in solving statistical issues is also related to solving problems using computational thinking patterns. This is because problem-solving activities involve critical mathematical abilities such as applying rules to non-routine problems, finding patterns, generalizing, and others (Rahmadhani & Mariani, 2021). Prospective mathematics teachers are continuously trained to use Computational Thinking patterns or indicators in learning, such as decomposition, abstraction, thinking and formulating algorithms, and forming solution patterns for similar problems. These four patterns are used to analyze the extent to which students solve problems in mathematics or find out at what stage students often make mistakes (Swaid, 2015).

There have been several studies regarding the exploration of computational thinking skills of prospective mathematics teachers, such as computational thinking skills on geometric problems (Maharani et al., 2021), Diophantine Linear Equation Problems (Aminah et al., 2022), Linear Equation in Two Linear Problems (Muthma'innah, 2023), computational thinking seen from Entrepreneur Character (Aminah et al., 2023), and computational thinking analysis from Prior Knowledge (Sari et al., 2024). Of the existing research, no one has studied the computational thinking of Prospective Mathematics Teachers in solving statistical problems.

Based on the explanation before, research was conducted to determine the level of Computational Thinking abilities of prospective Mathematics Teachers, especially in the Mathematics Education Study Program, especially students who are programming the Statistical Methods Course. The results of this research can also help teachers develop learning that can improve students' computational thinking skills in mathematics education study programs to produce quality mathematics teachers.

## Research Method

This research uses a descriptive design with a quantitative approach. The research subjects were 88 prospective mathematics teachers from the Mathematics Education study program at the Faculty of Teacher Training and Education, Lambung Mangkurat University. The student is taking the Statistical Methods course in the even semester of the 2022/2023 academic year. The object of the research is computational thinking skills, which are measured using a test in the form of essay questions.

The computational thinking ability test questions for prospective mathematics teachers in the statistical methods course consist of three statistical problems related to the use of the t-test, ANOVA test, and multiple regression test. The test was categorized as valid based on the assessment by the lecturer who taught the statistical methods course. Quantitative data in test results are analyzed based on computational thinking ability indicator scores. Computational thinking indicators used in this research include decomposition, abstraction or pattern recognition, algorithm development, and generalization, the description of which is adapted from (Susanti & Taufik, 2021).

Students' computational thinking skills are categorized using the average score and standard deviation. The categorization of computational skill scores was adapted from the categorization formula (Arikunto, 2013) presented in Table 1.

**Table 1. Category of Computational Thinking Skills**

Category	Score
Very Good	$X \geq (M + 1.5 Sdi)$
Good	$(M + 0.5 Sdi) < X < (M + 1.5 Sdi)$
Enough	$(M - 0.5 Sdi) < X < (M + 1.5 Sdi)$
Low	$(M - 1.5 Sdi) < X < (M - 0.5 Sdi)$
Sufficient	$X < (M - 1.5 Sdi)$

**Description:**

M = Average Score

Sdi = Standart Deviation

Based on this categorization, categorization will also be obtained for each indicator of computational thinking skill.

**Results and Discussion**

Computational thinking skill test questions were given to students in statistical methods courses in classes A, B, and C for the 2022/2023 academic year. With a total of 88 prospective teacher students on June 16, 2023. Due to the large number of students, this test was carried out in two rooms simultaneously. The time given for students to complete a test containing three statistical problems is 100 minutes. This test is a closed book, but students can use a calculator as a calculation tool.



**Figure 1. Prospective Mathematics Teacher When Taking Tests**

### Computational Thinking Skill

The test results are in the form of student answers, which are then checked and given a score for each problem according to the rubric that has been prepared. Students' computational thinking skills were analyzed descriptively by referring to each student's total score for the three problems. Based on the scores from measuring the answers of 88 students, data was obtained regarding the maximum score, minimum score, average score obtained by students, and standard deviation as presented in Table 2 below.

**Table 2. Computational Thinking Skill**

Number of Students	$\bar{X}$	$x_{min}$	$x_{maks}$	$S_{di}$
88	30,25	8	48	11,5

Based on Table 1, a table categorizes the Computational Thinking Skills along with the number of students for each indicator as presented in Table 3.

**Table 3. Category of Prospective Mathematics Student on Computational Thinking**

Category	Score	Number of Students	Persentase
Very Good	$X \geq 47,5$	2	2,27%
Good	$36 < X < 47,5$	28	31,82%
Enough	$24,5 < X < 36$	34	38,64%
Low	$13 < X < 24,5$	17	19,32%
Sufficient	$X < 13$	7	7,95%
Total		88	100%

Based on Table 3, most of the computational thinking of prospective mathematics teacher students is categorized as sufficient, followed by the Good category. However, it was still found that the category of students whose computational thinking was categorized as low and very low, which, if added up, was a quarter of all test takers. Students in the good category generally can fulfil the indicators of decomposition, abstraction, and algorithmic preparation, which are key components of computational thinking (Brennan & Resnick, 2012; Shute et al., 2017). These findings align with studies emphasizing the importance of developing computational thinking early in teacher education to effectively prepare them to integrate CT into classroom practices (Yadav et al., 2016). The test results scoring for each computational thinking skill indicator are presented in Table 4.

**Table 4. The Results of Each Indicator on the Computational Thinking Ability Test**

Indicator	$x_{min}$	$x_{maks}$	$\bar{X}$	$S_{di}$	Percentage score above average
Decomposition	1	12	8,76	2,25	69,32
Abstraction	1	12	7,58	3,18	46,59
Algorithm Development	1	12	8,3	3,04	52,27
Generalization	0	12	5,9	3,32	37,50

Based on the data in Table 4, the minimum average value obtained for the generalization indicator is 5.9, and the maximum average value obtained for the decomposition indicator is 8.76. So, students make many mistakes when using



generalization indicators. These results are similar to the research results from (Yuntawati et al., 2021). In solving the first and second questions in their research, respondents were able to solve problems using the Computational Thinking component, starting with decomposition, abstraction, and algorithm. Meanwhile, the generalization component was not visible in the problem-solving process, even though several respondents answered incorrectly. The results of the computational thinking ability test analysis are as follows:

#### 1. Decomposition

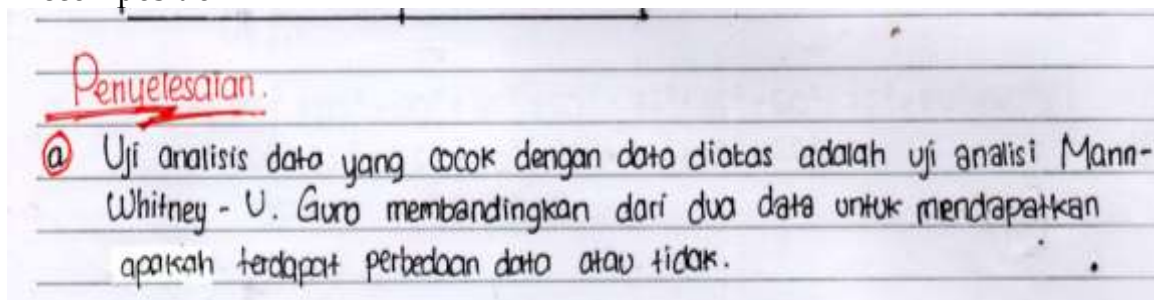


Figure 2. Decomposition Process

Based on Figure 2, students can decompose the problem by stating the appropriate analysis to use on the data available in the problem. Students are also able to state the reasons. The decomposition indicator shows the best results compared to other indicators, with an average value of 8.76, with a percentage of 69.32%. This shows that students are skilled at breaking down complex problems into smaller parts. Decomposition is a crucial first step in computational thinking because it allows students to understand the basic components of a problem before looking for a solution. A high score on this indicator reflects that the teaching methods in statistical methods courses are successful in helping students recognize and manage elements of larger statistical problems. However, to ensure a more profound understanding, it is recommended that more exercises that integrate different types of problems be provided so that students can continue to hone their decomposition skills in various contexts.

Decomposition is a key component of computational thinking, referring to the ability to break down complex problems into smaller, more manageable parts. This skill enables students to systematically analyze and solve each sub-problem without being overwhelmed by the overall complexity. According to Shute, Sun, and Asbell-Clarke (2017), decomposition enhances problem-solving ability and facilitates knowledge transfer to new contexts, as students learn to identify recurring structures within problems. Wing (2006) also emphasized that decomposition is a foundational step in computational thinking, as it paves the way for applying other strategies such as abstraction and algorithmic thinking. Mastering decomposition allows learners to understand problem elements better and supports the development of more effective and scalable solutions.

## 2. Abstraction and Algorithm Development

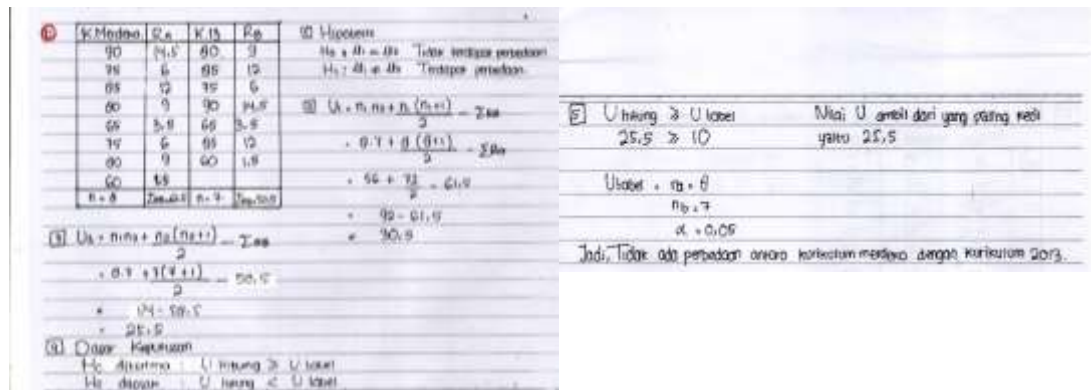


Figure 3. Abstraction and Algorithm Development Process

In Figure 3, students can carry out pattern recognition. That is, they can carry out steps in solving the problem given and use formulas appropriate to the data analysis being asked. Besides, students are also able to prepare algorithms, namely, they can do calculations correctly based on existing formulas.

Abstraction in computational thinking is the process of filtering out the unnecessary details and focusing on the important information needed to solve a problem. This step allows learners to simplify complex problems by identifying patterns, structures, or relationships relevant to the task. According to [Wing \(2006\)](#), abstraction is a fundamental aspect of computational thinking that supports efficient problem solving and algorithm design. It helps students focus on the general principles behind the problem rather than getting lost in specific details. However, abstraction is often one of the more challenging skills to master, especially in statistical or mathematical contexts, because it requires higher-order thinking to determine which information is essential. As noted by [Yadav et al. \(2014\)](#), teaching abstraction effectively requires providing students with diverse problem sets and explicit instruction on analyzing and reducing complexity. Encouraging students to explain their reasoning and make decisions about which data is relevant can enhance their abstraction skills over time.

In the abstraction or pattern recognition indicator, students obtained an average score of 7.58 with a percentage of 46.59%, which is relatively lower than important patterns and exclude irrelevant information, a skill that is essential in simplifying statistical problems. This value shows that most students can recognize important patterns and elements in the problem, but may still have difficulty distinguishing between relevant and irrelevant information. This aspect can be improved by presenting more case studies with varying variable complexity so that students get used to filtering information more efficiently and effectively. In line with the research ([Hapizah et al., 2024](#)), 21.43% of students succeeded in linking the concepts or formulas they had learned to problem-solving tasks, in contrast to the findings of ([Rijal Kamil et al., 2021](#)), which indicated greater proficiency. High in this field. Most students persist in listing procedural steps instead of integrating relevant concepts into their answers, as documented in ([Supiarmo et al., 2021](#)). Students' difficulty is linked to their understanding of mathematical concepts, which is essential. As facilitators in learning,

lecturers should understand that the material taught to students is not just about memorization (Muthma'innah, 2023).

Algorithm development is a critical stage in computational thinking where students design step-by-step procedures to solve problems efficiently and systematically. In the context of statistical learning, this involves selecting appropriate formulas, organizing data, and executing calculations in the correct order. According to Shute et al. (2017), algorithmic thinking enables students to transition from conceptual understanding to practical application, allowing them to automate problem-solving processes.

The average value for the algorithm preparation indicator is 8.3 with a percentage of 52.27%, which shows that they can formulate solution steps systematically, even though the majority still make mistakes. Algorithm development is a skill that requires students to outline the steps to solve a problem sequentially and logically. However, the minor errors still discovered indicate room for improvement, especially in ensuring that each algorithm step is executed correctly and consistently. Exercises involving a more varied statistical problem can strengthen students' algorithmic skills. In line with the research (Hapizah et al., 2024) and (Rahmadani et al., 2018), some face challenges in documenting sequential steps comprehensively in problem-solving algorithms. The results of interviews in research (Supiarmo et al., 2021) show that some students experience difficulties in understanding problems, which affects their ability to design and then carry out problem-solving processes as required by algorithmic indicators.

### 3. Generalization

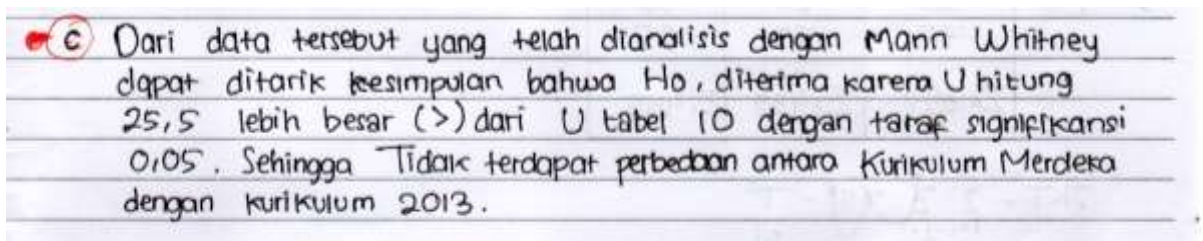


Figure 4. Generalization Process

In Figure 4, students can generalize. They can make conclusions correctly based on the steps they have taken. The generalization indicator recorded the lowest average value, namely 5.9, with a percentage of 37.50%. This shows that students have difficulty concluding solutions that can be applied more widely based on the steps taken. Generalization is an important final step in computational thinking because this ability allows students to develop solutions that apply to one problem and similar problems in the future. This difficulty may be caused by a lack of practice in connecting the problem being solved to general patterns that can be applied more widely. In line with the research (Julianti et al., 2022), from the two people interviewed, it was found that the two subjects could not carry out the generalization stage. This is due to the subject's lack of understanding regarding determining the pattern's general shape. So the subject finds it difficult and gives up when faced with a problem that requires finding the general shape of the pattern, and prefers to use simple methods rather than



determining the general shape of the pattern. Therefore, the results of the generalization stage in this research are in line with previous research.

Generalization in computational thinking refers to identifying patterns, trends, or principles from specific problems and applying them to broader problems or contexts. Higher-order cognitive skills enable learners to extend their problem-solving abilities beyond the task. According to Grover and Pea (2013), generalization is crucial for developing adaptable and reusable solutions, a fundamental aim of computational thinking education. When students can generalize, they are not merely solving isolated problems but are learning how to transfer their strategies and knowledge to new and unfamiliar situations. However, this skill often requires explicit instruction and repeated practice, as students may struggle to recognize abstract structures or commonalities across different problems without guidance (Selby & Woollard, 2013). Therefore, supporting generalization through varied examples and reflective activities can enhance students' computational proficiency.

## Conclusion

The computational thinking skills of prospective mathematics teachers in solving statistics problems were in the Very Good category with a percentage of 2,27%, the Good Category was 31,8%, the Enough category was 38,64%, the Low category was 19,32%, and the Deficient category was 7,95%. The highest average score results in the Decomposition indicator, logarithmic preparation, abstraction, or pattern recognition, and the lowest average score results in the generalization indicator. Researchers suggest that ongoing research must be conducted to improve students' computational thinking skills. It is necessary to look for factors influencing students' computational thinking skills.

## Acknowledgments

Thank you to Lambung Mangkurat University for funding in the Program Dosen Wajib Meneliti (PDWM) in 2023.

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