Cognitive Development Journal
Vol. 2, No. 2 (2024), pp. 87-95 | e-ISSN: 3025-8693
Homepage: https://ojs.edutechpublishing.com/index.php/cognitive

Pre-Service Teachers and Computational Thinking: Designing Meaningful Learning in Higher Education

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Received: December 1, 2024; Revised: December 24, 2024; Accepted: December 29, 2024; Published: December 31, 2024

ABSTRACT
This study aims to understand the students' computational thinking skills in statistics .The type of research is descriptive with a qualitative approach. The data collection techniques in this study include 1) Tests; 2) Interviews; 3) Documentation; and 4) Validation Sheets. The data analysis in this study involves: 1) Data condensation; 2) Data presentation; 3) Verification; and 4) Conclusion drawing. The validity of the data in this study is ensured using technique triangulation. Subjects were selected using purposive sampling. The instruments used were two statistical problem-solving questions. The results showed that in solving the first and second questions, the respondents could address the problems using the components of Computational Thinking, starting with decomposition, abstraction, and algorithm tasks. However, the pattern recognition component was not evident in the problem-solving process, even though some respondents gave incorrect answers. This was because the respondents did not fully understand the questions. They only read the questions once or twice, so the information was not fully comprehended. Additionally, the respondents only considered the simplest path and overlooked more complex paths in solving the second question. Students can carry out abstraction and algorithmic tasks, but they still struggle with decomposition and pattern recognition.
Keywords: student, mathematics, statistic, computational thinking, ability

INTRODUCTION

In the digital age, the integration of computational thinking (CT) into mathematics education has become increasingly vital. As statistical literacy grows in importance across academic disciplines and professional domains, the need for students particularly future mathematics educators—to master not only statistical concepts but also computational strategies become paramount. Computational thinking, as conceptualized by Wing (2006), refers to a problem-solving process that includes characteristics such as logical analysis, pattern recognition, abstraction, decomposition, and the design of step-by-step algorithms. These skills are foundational for engaging complex, data-rich problems that are central to both modern education and professional practice.

This study was conducted in recognition of the pivotal role CT plays in fostering deeper understanding and adaptability when students confront mathematical problems, particularly in the field of statistics. Statistical problems are often ill-structured and multifaceted, demanding a sophisticated interplay of conceptual understanding and procedural fluency. Through computational thinking, students are expected to approach these problems systematically breaking them down into manageable parts (decomposition), identifying relevant structures or regularities (pattern recognition), filtering essential information from noise (abstraction), and applying logical sequences or procedures to reach solutions (algorithmic thinking).

However, while educational policies and curricular frameworks such as PISA 2021 and Indonesia's Merdeka Curriculum have begun to emphasize computational thinking as a core 21st-century skill, empirical evidence on how students particularly prospective teachers internalize and apply CT components in specific domains like statistics remains limited. Most existing studies focus on general problem-solving or programming contexts, often neglecting the nuanced applications of CT within mathematical subfields.

This research specifically investigates how undergraduate students in a mathematics education program students who are being prepared as future mathematics teachers demonstrate computational thinking skills in the context of solving statistical problems. By analyzing student responses to two open-ended statistical problems, the study aims to uncover the extent to which each CT component is activated during problem-solving. Early findings indicate that while students often succeed in applying abstraction and algorithmic thinking, they tend to struggle with decomposition and, most notably, with pattern recognition.

Understanding the profile of students' CT skills not only provides insight into their current problem-solving competencies but also serves as a diagnostic tool for teacher educators. With this understanding, instructional interventions can be more precisely designed to target underdeveloped areas of computational thinking. Moreover, since these students will eventually become the facilitators of learning for future generations, fostering comprehensive CT abilities in them is a strategic investment in long-term educational quality.

Therefore, the objective of this study is to explore and analyze the computational thinking skills of mathematics education students in solving problems in statistics. The focus is particularly on how they utilize (or fail to utilize) the core CT components decomposition, pattern recognition, abstraction, and algorithmic thinking and what these reveals about their readiness to engage with statistical problem-solving in both academic and pedagogical settings.

2. LITERATURE REVIEW

In this era of technological advancement, students need to have technology-based skills. The abilities that can keep up with technological developments are computational and mathematical thinking skills. This is demonstrated by the addition of the computational thinking category in the Program for International Student Assessment (PISA) 2021 (Kusaka, 2021). Computational thinking emerged in the 1950s and 1960s, embodying a mindset aimed at framing problems as transformations and discovering algorithms to execute these transformations. It was designed to incorporate high-level abstract thinking, utilizing mathematics to create algorithms and identify optimal solutions to various problems.

Additionally, the Indonesian Minister of Education, Culture, Research, and Technology has introduced a new policy on the Indonesian curriculum in 2022, incorporating computational thinking (Apriani et al., 2021). Furthermore, the World Economic Forum has stated that critical thinking is a skill needed in the next five years. Students require these skills as they are essential for training students to think logically, critically, and systematically (Yasinta et al., 2020).

The National Science Teacher Association (NSTA) states that 21st-century skills, such as thinking skills and problem-solving skills, can be developed in the learning process. This aligns with the goals of mathematics education outlined by the National Council of Teacher Mathematics (NCTM), which include developing the following skills: (1) problem-solving; (2) reasoning and proof; (3) communication; (4) connection; (5) representation (Rahmadhani & Mariani, 2021).

Computational thinking and critical mathematical thinking skills are closely related. Computational thinking skills often require a strong understanding of basic mathematics because many algorithms and computational processes rely on mathematical concepts. Computational tools are not just valuable for adult scientists; they're also becoming more prevalent in science classrooms. These tools have been demonstrated to enhance the understanding of science concepts among students (Aksit, O., & Wiebe, 2020; Dickes, Amanda Catherine; Sengupta, Pratim; FARRIS, AMY VOSS; BASU, 2016; Hutchins, N. M., Biswas, G., Maróti, M., Lédeczi, Á., Grover, S., Wolf, R. & K., 2020; Malone, K. L., Schunn, C. D., & Schuchardt, 2018; Peel, A., Sadler, T. D., & Friedrichsen, 2019).

Additionally, both computational thinking and critical mathematical thinking skills require systematic and logical thinking processes. They both involve the ability to formulate problems, plan solution approaches, conduct analysis, and evaluate results (Setyautami, 2020; Ziarati et al., 2022). This creates a similarity in the problem-solving approach between these two skills. Thus, computational thinking can not only be used as a tool to solve mathematical problems but also to train and sharpen critical mathematical thinking skills. Integrating these two skills in mathematics education can help students develop a deeper understanding of mathematical concepts and the ability to solve problems systematically and effectively (Mauliani, 2020; Yuntawati et al., 2021). This involves the thinking process of formulating problems and solutions so that the solutions are effectively presented and can be implemented by an information processor to understand the computational thinking approach in addressing problems and developing solutions to solve similar issues if needed (Abdul-Rahman Al-Malah et al., 2020; Kamil et al., 2021).

Computational Thinking and mathematics have a reciprocal relationship, using Computational Thinking to enrich the learning of mathematics and science, and applying mathematical and scientific contexts to enhance Computational Thinking skills. This also improves mastery of number sense and arithmetic abilities, which are influenced by thinking styles, attitudes toward mathematics, and cognitive habits (Maharani et al., 2019; Masfingatin & Maharani, 2019).

One area of study closely related to computational thinking skills is statistics. In learning, students must recognize or identify certain patterns or rules. By recognizing patterns, students can break down problems into smaller, more manageable parts. Additionally, students are also asked to create models from mathematical problems. Students must also possess the ability to understand problems and their solutions. With these skills, students will find it easier to generalize solutions to various problems. The process of identifying patterns and building patterns also requires algorithmic thinking (Rosali & Suryadi, 2021). In this study, the components of computational thinking skills are referred to as computational skills components, as explained by Hunsaker (Hunsaker, 2020). The components are problem decomposition, pattern recognition, abstraction and generalization, and algorithmic thinking. Previous research on computational thinking has targeted secondary school students and teachers, while the knowledge transfer subjects with various methods are teachers, who need to possess and master various skills, including computational thinking skills. Therefore, the subjects chosen for this study are prospective mathematics teachers, which makes this research different from previous studies.

The Mathematics Education Research Program at Veteran Bangun Nusantara University is one of the training programs for prospective mathematics teachers, responsible for equipping them with various skills, including computational thinking skills. These skills will become essential when they eventually become teachers, enabling their students to develop strong computational thinking abilities. The first step in preparing strategies to enhance and develop the computational thinking skills of future mathematics teachers is to first understand and analyze the computational thinking skills of the students.

METHODS

The research conducted is a descriptive study with a qualitative approach and uses a literature review as a research technique. The respondents involved in the study are six mathematics education students from Veteran Bangun Nusantara University. The characteristics of the respondents are that they have completed a Statistics course. The technique used to select the respondents is purposive sampling. This study employs a specific instrument to measure four computational thinking abilities: decomposition, pattern recognition, abstraction, and algorithmic thinking, which are assessed through five descriptions forming the test (Fajri et al., 2019).

The research design includes a pretest to assess statistics skills and a diagnostic test to evaluate computational thinking abilities. The triangulation method used is methodological triangulation, which compares the methods of the diagnostic test and pretest with interview data. The researcher has conducted preliminary observations during the Statistics learning process. Subsequently, students were given a pretest followed by a diagnostic test on probability. Data from the pretest and diagnostic test were reduced to identify subjects for further investigation, and interviews were conducted to gain deeper insights into their computational thinking abilities. Methodological triangulation was then applied to the data from the diagnostic tests and interviews.

RESULTS AND DISCUSSION

Results

The research involved two statistical problem-solving questions designed to assess students' Computational Thinking (CT) abilities. These questions were intended to evaluate how well students could apply the different components of CT namely, decomposition, abstraction, algorithmic thinking, and pattern recognition, when tackling statistical problems.

The Two Statistical Problem-Solving Questions: these questions required students to apply various CT components to analyze and solve statistical problems. The tasks likely involved breaking down complex problems (decomposition), identifying key elements and relationships (abstraction), developing step-by-step solutions (algorithmic thinking), and recognizing patterns within data (pattern recognition).

1. Decomposition, Abstraction, and Algorithmic Thinking
   a. Decomposition: The students were able to break down the problems into smaller, more manageable parts. This involves identifying different components of the problem and addressing each one separately. For example, in a statistical problem, this might mean separating data organization from data analysis.
   b. Abstraction: Students effectively abstracted the critical aspects of the problems, focusing on the most relevant information and filtering out unnecessary details. This process involves understanding the core of the problem without getting bogged down by extraneous data or complexities.

   c. Algorithmic Thinking: The students demonstrated the ability to formulate step-by-step procedures or algorithms to solve the problems. This might involve applying statistical formulas, creating sequences of operations, or developing a plan for analyzing the data.

2. Pattern Recognition: This component of CT was notably absent in the students' problem-solving processes. Pattern recognition involves identifying trends, regularities, or recurring themes within the data or the problem context. In statistics, recognizing patterns is crucial for making predictions, understanding relationships, and drawing conclusions. Despite the importance of this skill, students failed to demonstrate it in both questions. This deficiency could be attributed to a superficial engagement with the problems.
3. Misunderstanding of the Questions: The students' failure to recognize patterns might be linked to their inadequate understanding of the problem statements. It was observed that the students tended to read the questions only once or twice. This limited engagement with the questions likely led to an incomplete comprehension of the information presented. Without fully grasping the problem, students might have missed important clues or overlooked the need for deeper analysis, which is often required to identify patterns.
4. Simplistic Problem-Solving Approach: In solving the second question, many students opted for the simplest possible path to a solution. While simplicity can be beneficial, it can also lead to overlooking more complex, yet potentially more accurate, methods of solving a problem. By focusing solely on the simplest solution, students may have ignored alternative approaches that could have provided a better understanding of the problem or a more robust solution. Figure 1 shows the chart of CT component.

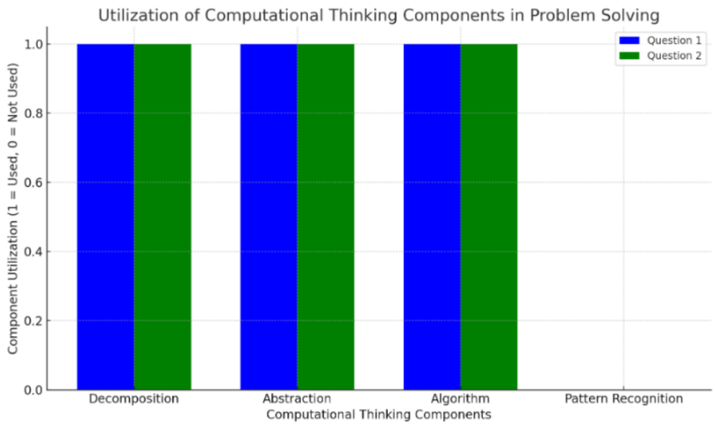

Figure 1. chart of CT component

Here's a bar chart representing the utilization of Computational Thinking components by students when solving the two statistical problems. The chart shows that students consistently used decomposition, abstraction, and algorithmic thinking in both questions, but pattern recognition was not evident in either case. This highlights a gap in their problem-solving approach, particularly in understanding and analyzing patterns within the problems.

Discussion

When students can perform abstraction and algorithmic tasks but struggle with decomposition and pattern recognition, it indicates specific strengths and weaknesses in their computational thinking skills. Here's a detailed explanation of what this means and the implications for their learning process:

1. Abstraction: If students are proficient in abstraction, they can effectively simplify complex problems. They understand what parts of a problem are important and can generalize from specific examples to broader concepts. For example, in statistics, they might recognize that a dataset's central tendency (mean, median, mode) is more critical than individual outliers when generalizing about the data.

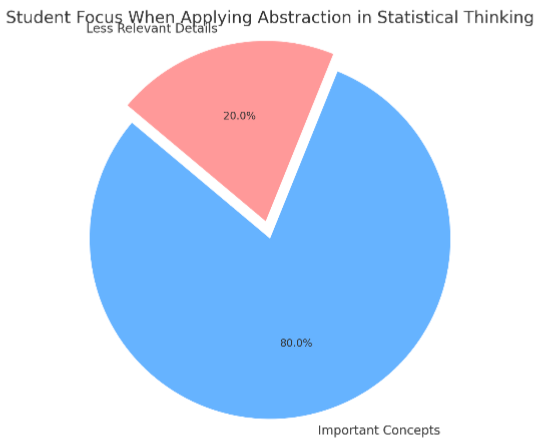

Figure 2. Student focus when applying abstraction

2. Algorithmic Thinking: Students who are good at algorithmic thinking can devise and follow structured approaches to solve problems. For instance, they might be able to apply a statistical formula to calculate standard deviation or create a procedure to clean and organize data systematically.
3. Decomposition: Students struggling with decomposition may find it difficult to identify and isolate different parts of a problem. Instead of breaking a problem into smaller tasks, they might try to solve it, leading to confusion or errors. For example, in a statistical analysis task, they might not separate data collection, data cleaning, and data analysis into distinct phases, causing them to become overwhelmed by the complexity.
4. Pattern Recognition: If students struggle with pattern recognition, they might miss important trends or fail to see connections between different elements of a problem. For instance, they might not recognize that a dataset exhibits a normal distribution, which is key to deciding the appropriate statistical tests to apply. This could lead to incorrect conclusions or the misuse of statistical methods.

In conclusion, while the students show promise in their ability to abstract and execute algorithms, their struggles with decomposition and pattern recognition indicate areas where additional support and practice are needed to ensure they can approach and solve complex problems comprehensively.

CONCLUSION

In analyzing the students' responses to the first and second questions, it was observed that they were able to utilize various components of Computational Thinking, including decomposition, abstraction, and algorithmic tasks. However, the pattern recognition component was noticeably absent in their problem-solving process, even when some students provided incorrect answers. This may be attributed to the students' limited understanding of the questions, as they tended to read the questions only once or twice, resulting in an incomplete comprehension of the information. Furthermore, the students often chose the simplest solution paths, neglecting more complex approaches in their attempts to solve the second question. Students can perform abstraction and algorithmic tasks, but they continue to have difficulties with decomposition and pattern recognition.

CONFLICT OF INTEREST

The author declares that there is no conflict of interest regarding the publication of this research. This study was conducted independently, without any financial or non-financial support that could influence the results or interpretations. All procedures and data interpretations were carried out objectively based on academic integrity and scientific principles. The university where the research was conducted (Veteran Bangun Nusantara University) and all participating students were involved solely for academic purposes, and no personal, commercial, or institutional interests have influenced the research outcomes.

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