

Examining prospective mathematics teachers' computational thinking through the lens of cognitive style

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ABSTRACT

The advancement of technology and the demands of the 21st century require prospective mathematics teachers not only to be proficient in content knowledge but also to possess adaptive computational thinking (CT) skills. This study aims to explore the CT abilities of prospective mathematics teachers based on their cognitive styles, namely field-independent (FI) and field-dependent (FD). A descriptive qualitative approach was employed, involving four prospective mathematics teachers selected through purposive sampling based on the results of the Group Embedded Figures Test (GEFT) and their initial CT abilities. Data were collected through CT problem-solving tasks, think-aloud protocols, semi-structured interviews, and direct observations, and were analyzed thematically. The findings reveal that all participants demonstrated competencies in the four dimensions of CT: decomposition, abstraction, pattern recognition, and algorithmic thinking. FI participants (S1 and S2) tended to exhibit CT with symbolic and reflective characteristics, such as symbolic-structural and reflective-tactical thinking. In contrast, FD participants (S3 and S4) displayed concrete-procedural and exploratory-conceptual CT, emphasizing numerical and contextual strategies. These differences highlight the influence of cognitive styles on the CT tendencies of prospective teachers. This study underscores the importance of developing CT training programs that are adaptive to students' cognitive styles in order to optimize their potential in mathematical problem-solving. The practical implications support the implementation of differentiated CT instruction that accommodates individual thinking preferences within mathematics teacher education.

INTRODUCTION

As information technology advances and drives global competition, countries need to prepare students with appropriate technical knowledge and communication skills to compete in the 21st century. One way to address this challenge is by incorporating Computational Thinking (CT) into the curriculum (Bower et al., 2017; Maharani et al., 2019). CT is one of the essential skills for successfully overcoming challenges in a complex society shaped by technological advances (Kale et al., 2018).

CT is a fundamental skill for students in education, equivalent to reading and numeracy (Zhong et al., 2015). This is supported by Maharani et al. (2019), who state that integrating CT into the school curriculum generally enhances students' ability to think abstractly, develop algorithms, and apply logical reasoning. As a result, students are better equipped to tackle complex and open-ended problems. Activity-based learning strategies have been identified as an effective approach to improving adolescent cognition and guiding learning through manipulative activities and verbal

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interactions (Cho & Lee, 2017). CT is regarded as a key competency because students not only need to master subjects influenced by computing, but also must be able to apply them in everyday situations and in the global economic context.

Mathematics is one of the essential components of the school curriculum. Therefore, the integration of CT into mathematics instruction can enhance students' conceptual understanding of mathematical content. Mathematics learning activities often require hands-on experience that help students develop their problem-solving skills (Maharani et al., 2021; Sung et al., 2017). CT and mathematics share a mutually reinforcing relationship, where computational methods can enrich learning in mathematics and science. Conversely, mathematical and applied science context can be used to deepen students' understanding and application of computational concepts (Budyastomo & Yusuf, 2024).

The primary reason for introducing CT in mathematics classrooms stems from the growing understanding that computerization is increasingly being applied across various fields of work. Mathematical ability is considered a key factor in predicting students' learning capacity. Gadanidis (2017) and Rambally (2017) argue that mathematical thinking plays an important role in the development of CT, as the process of solving mathematical problems is inherently constructive (Benakli et al., 2017; Junsay, 2016; Maharani et al., 2020). This constructive process requires an analytical perspective to solve problems that are both unique and fundamental to students. On the other hand, to teach CT effectively, teachers must have a comprehensive understanding of CT. Mathematics teachers need to consistently integrate CT into their instructional practices. Therefore, it is necessary to examine and understand the CT abilities of prospective mathematics teachers, so that when they enter the teaching profession, they are truly prepared.

However, the implementation of CT in mathematics teacher education in Indonesia still faces various challenges. Research by Pertiwi et al. (2025) indicates that the integration of CT in mathematics learning across Indonesian educational institutions remains limited and inconsistent. This issue is compounded by teaching approaches that tend to be uniform and do not take into account individual differences in cognitive styles. Cognitive styles, particularly field-dependent (FD) and field-independent (FI), play an important role in how individuals process information and solve problems. Nicolaou and Xistouri (2011) found that students with FI cognitive styles demonstrated stronger abilities in structuring and solving mathematical problems compared to their FD counterparts. In the Indonesian context, a study by Hardiansyah et al. (2024) revealed that FI students are more capable of representing mathematical concepts abstractly, while FD students rely more on concrete representations. Unfortunately, current CT instructional approaches have not yet adapted to these cognitive style differences. As a result, the full potential of individuals in developing CT skills cannot be optimally realized.

Previous research has shown that the integration of CT in mathematics education has been a major focus over the past decade, particularly in the context of K-12 education and teacher training. A systematic review by Ye et al. (2023) highlights that CT-based approaches, such as project-based learning and visual programming (e.g., Scratch), can enhance the understanding of mathematical concepts such as geometry, patterns, and algorithms. However, the study also notes that integration of CT is not always equally successful across all areas of mathematics and that challenge remain in aligning computational thinking with traditional mathematical reasoning.

In addition, a literature review by Mohmad and Maat (2023) found that despite growing interest in CT-related activities among mathematics teachers, the number of studies specifically addressing CT practices in mathematics education remains limited. Most existing research has focused on the use of programming and robotics as tools to develop CT skills; however, few have explored how individual cognitive styles influence the application of CT in mathematics instruction. Research conducted by Reichert et al. (2020) shows that mathematics teachers' CT skills were still weak prior to receiving training. However, the study did not address aspects of teachers' cognitive styles, even though their responses and adaptations to CT approaches are likely influenced by the way they process information (e.g., reflective vs. impulsive), their visual or verbal preferences, and their tendency toward global or analytical thinking.

Previous studies have highlighted the importance of integrating Computational Thinking (CT) into mathematics education and the need for approaches tailored to the individual characteristics of

Table 1
CT indicators

Aspect	Characteristics/Indicators
Decomposition	The ability to break down complex problems into simpler parts that are easier to understand and solve
Abstraction	The ability to identify and focus on relevant information by deciding which elements to use or disregard
Pattern Recognition	The ability to identify similarities and patterns in order to formulate general solutions applicable to various problems, including the use of variables
Algorithmic	The ability to design a step-by-step process or set of actions to solve problems systematically

teachers. However, there remains a lack of understanding regarding how the cognitive styles of prospective mathematics teachers influence the development and integration of CT. Therefore, by exploring the relationship between cognitive style and CT ability, this study aims to provide valuable new insights for designing more effective and personalized teacher training programs, while also enriching the existing literature on the integration of CT in mathematics education.

This research offers novelty by integrating two important domains that are still rarely explored explicitly in the literature: Computational Thinking (CT) and cognitive style, particularly in the context of prospective mathematics teachers. To date, most CT-related research in mathematics education has focused on evaluating the effectiveness of CT-based instructional approaches or developing CT-oriented educational tools. Meanwhile, studies that examine how variations in cognitive style influence CT abilities—especially among future mathematics teachers—remain scarce. Using an exploratory approach, this study aims to investigate how field-independent and field-dependent cognitive styles affect individuals' tendencies to develop CT components such as decomposition, abstraction, and algorithms. These findings are expected to serve as a foundation for designing teacher training programs that are more adaptive and responsive to individual differences, and to contribute to the advancement of differentiated CT learning models in mathematics education. The CT indicators used in this study are presented in Table 1.

The research question is what is the level of CT ability in prospective mathematics teachers? What are the cognitive styles that prospective mathematics teachers have? What is the relationship between cognitive style and the CT ability of prospective mathematics teachers? What are the challenges and potentials in the development of CT based on different cognitive styles?

METHODS

This section describes the approaches, strategies, and procedures employed in the research to achieve the objectives and address the research questions. The study aims to explore the computational thinking (CT) abilities of prospective mathematics teachers based on their cognitive styles.

Design

This study employs a descriptive qualitative approach aimed at providing an in-depth description of the CT abilities of prospective mathematics teachers based on their cognitive styles. This approach was selected because it allows for a holistic understanding of thinking dynamics, problem-solving strategies, and individual characteristics that cannot be fully captured through a quantitative method. The research emphasizes a contextual understanding of how prospective teachers think when solving CT-based problems and how specific cognitive styles influence their construction of solutions.

Participants

The subjects in this study were 30 prospective mathematics teachers enrolled in the final semester of the Mathematics Education study program at Universitas PGRI Madiun. Subject selection

was carried out using purposive sampling based on the following criteria: (1) demonstrating computational thinking (CT) when solving the given mathematical problem, and (2) willingness to participate in the entire data collection process, including completing tests, CT tasks, and interviews. The selection process began with administering the Group Embedded Figures Test (GEFT) to identify students' cognitive styles. Next, students were given a complex mathematical problem designed to measure their CT ability. In the third step, subjects were selected based on the criteria above for each cognitive style.

From the results, it was found that 9 students had a field-independent (FI) cognitive style, and 21 students had a field-dependent (FD) cognitive style. Based on this categorization, two students were selected from each cognitive style to become research subjects. Subjects S1 and S2 were categorized as FI, while S3 and S4 were categorized as FD.

Data collection

Data collection was conducted using several techniques and instruments. First, to identify the participants' cognitive styles, the researchers used a Likert-scale-based cognitive style questionnaire developed from relevant literature, along with visual tests such as the Group Embedded Figures Test (GEFT) to classify participants as either field-dependent or field-independent. Second, to assess CT abilities, participants were given CT-based problem-solving tasks that encompassed four main components: decomposition, abstraction, pattern recognition, and algorithms. While completing these tasks, participants were instructed to use the think-aloud technique, which involves verbally expressing their thought processes in real time. This technique enabled researchers to directly capture the cognitive strategies employed by participants during task completion. The following is the mathematical problem given to the subjects.

A pastry shop has 72 doughnuts that will be packed into boxes of small (6 fills), medium (9 fills), and large (12 fills). With the availability of three box sizes, how many boxes do you need for all the donuts to be packed? Also, if all the boxes used are fully filled, are there any donuts left out of the total 72 donuts that the cake shop has?

In addition, semi-structured interviews were conducted after the assignments to gain deeper insight into the participants' understanding of CT concepts and their reflections on the strategies used. These interviews also aimed to explore their perceptions, challenges, and thinking habits when dealing with technology-based mathematics problems. As a complement, direct observations were carried out by the researchers during the CT task process, supported by field notes that recorded non-verbal behaviors, spontaneous responses, and participants' engagement in their thought processes. The data collection flow is presented in [Figure 1](#).

Data analysis

The data obtained were analyzed using a thematic analysis method, which involved identifying themes that emerged from interview transcripts, observation notes, and assignment documentation. The analysis was carried out in three main stages: (1) data reduction, the process of sorting and simplifying the data into initial thematic codes; (2) data presentation, which involved grouping information based on cognitive style categories and CT dimensions; and (3) drawing conclusions, an interpretive process that connects emerging patterns in the data and narrates them as the key research findings.

To ensure data validity, several verification strategies were implemented. Triangulation was conducted by comparing data from various sources, including test results, CT assignments, interviews, and observations. In addition, member checking was performed by seeking confirmation from participants regarding the researchers' interpretations to ensure the findings accurately reflected their experiences. The researcher also conducted peer debriefing with supervisors or colleagues to test the strength of interpretations and reflections. The entire process was supported by a well-documented audit trail to maintain the transparency and replicability of the study. Through this approach, it is expected that the research will make a significant contribution to understanding

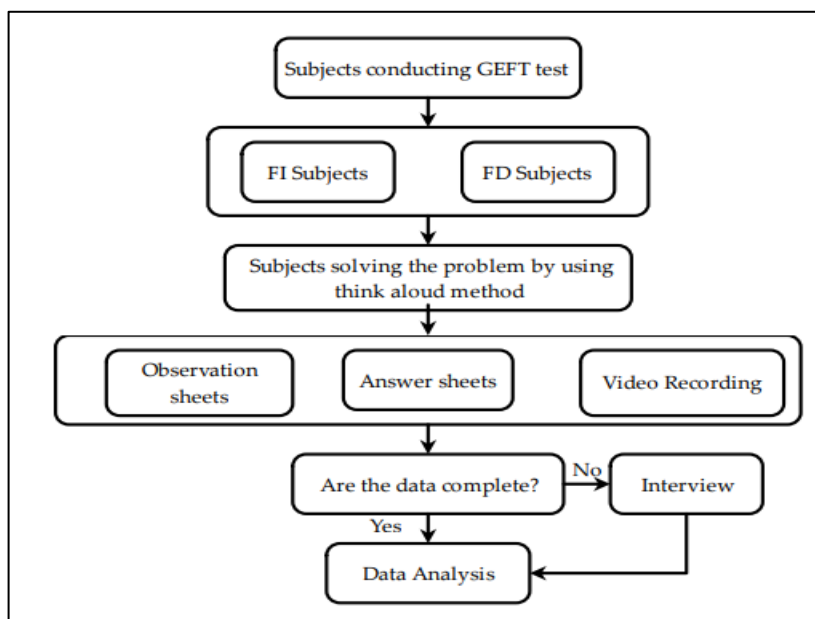


Figure 1. The data collection flowchart

how cognitive styles influence the computational thinking of prospective mathematics teachers, and serve as a basis for designing more adaptive and effective training and learning strategies.

FINDINGS

The results showed differences in CT between FI (Subjects S1 and S2) and FD (Subjects S3 and S4). All subjects met the CT criteria, but Subjects S1 and S2 showed different tendencies compared to Subjects S3 and S4. FI subjects tended to be analytical and reflective, while FD subjects were more practical and focused on numerical strategies.

Decomposition

In the decomposition stage, all subjects broke down complex problems into simpler ones, but differences were observed among the four subjects. Even subjects with the same cognitive style demonstrated different ways of simplifying the problems.

FI subjects (S1 and S2)

Figure 2 shows that S1 breaks down the problem of "arranging 72 donuts into different types of boxes" into: (1) identifying important information, such as the number of donuts per box (6, 9, 12); (2) assigning variables (n , m , q , r) to build the logical structure of the calculation; and (3) dividing the task into three sub-calculations based on the type of box. Through this approach, S1 systematically identifies the main sub-problems and breaks them down into manageable components. This reflects a well-developed and logical decomposition ability.

While S2 starts by identifying the total number of donuts (72) and systematically dividing them into three types of boxes. He used a numerical approach by dividing 72 by 3 to get 24 donuts, making it easier to allocate them to all box types. Then, S2 attempted to distribute the 24 donuts into each type of box (6, 9, and 12) separately and in a structured manner. S2 demonstrated strong decomposition skills, as shown by breaking down the main problem into three focused sub-calculations (small, medium, and large boxes). He also considered special conditions to manage any leftover donuts.

Based on this, both S1 and S2 demonstrate strong decomposition skills. However, S1 is more analytical, while S2 is more numerical. This indicates that although both can solve problems effectively, the approaches they use differ according to their respective thinking tendencies. S1 tends to use symbolic representations and general models, whereas S2 relies more on concrete calculations and straightforward operational strategies.

misal : n = banyaknya
 m : jumlah keseluruhan donat (yang dibagi)
 q : banyak kotak yang dibutuhkan
 r : sisa

maka: 72 donat kita bagi menjadi 3 kelompok yang sama, karena ad 3 macam
 $72 : 3 = 24$

→ kotak kecil : $m = q \cdot n + r$ } Jadi, dibutuhkan kotak kecil sebanyak
 $24 = 4 \cdot 6 + 0$ 4 kotak

→ kotak sedang : $m = q \cdot n + r$ } Jadi, dibutuhkan kotak sedang sebanyak
 $24 = 2 \cdot 9 + 6$ 2 kotak, karena sisa 6 maka dapat
 kita masukkan pada kotak kecil.

→ kotak besar : $m = q \cdot n + r$ } Jadi, dibutuhkan kotak besar sebanyak
 $24 = 2 \cdot 12 + 0$ 2 kotak.

Figure 2. The process decomposition of subject S1

Translate: example : n = many

m = total amount of donuts (divided)

q = many boxes needed

r = leftover

so : we divide 72 donuts into 3 equal groups, because there are 3 types

$$72 : 3 = 24$$

- | | | |
|--------------|--|-----------------------------------|
| • Small box | $m = q \cdot n + r$
$24 = 4 \cdot 6 + 0$ | } So, four small boxes are needed |
| • Medium box | $m = q \cdot n + r$
$24 = 2 \cdot 9 + 6$ | |
| • Large box | $m = q \cdot n + r$
$24 = 2 \cdot 12 + 0$ | |
- So, two medium boxes are needed, because the remaining six donuts can be placed in a small box
- So, two large boxes are needed

FD subjects (S3 and S4)

S3 begins by breaking down the number of donuts (72) according to the size of the boxes (6, 9, and 12), and calculating how many donuts each box size can hold if filled with a certain number of boxes: $6 \times 3 = 18$, $9 \times 2 = 18$, and $12 \times 3 = 36$. Then, S3 adds the results ($18 + 18 + 36 = 72$), thereby confirming that all the donuts have been distributed. After that, S3 compiles three steps to solve the problem: fill the large boxes first, then the medium ones, and finally the small ones. This step demonstrates logical sequencing in handling sub-problems. S3 exhibits good decomposition ability by breaking the problem into concrete units based on capacity and designing systematic steps to solve the entire problem.

S4 begins by stating that the 72 donuts will be divided into three groups of 24 donuts each, which are then placed into three different box sizes (small, medium, and large). Then, he calculates the distribution of the 24 donuts for each box type: $24 \div 6 = 4$ with no remainder (small), $24 \div 9 = 2$ with a remainder of 6 (medium), $24 \div 12 = 2$ with no remainder (large). This shows that S4 has systematically divided the problem into segments based on box size. S4 demonstrates good decomposition skills by organizing the solution steps into logically relevant sub-units.

Based on this, both S3 and S4 demonstrate good decomposition skills, but there are differences between the two. The difference lies in the direction of their decomposition approach: S3 focuses on the capacity of each type of box, while S4 emphasizes the equal distribution of the total donuts first. In other words, S3 uses a bottom-up approach (starting from box capacity), whereas S4 applies a top-down approach (starting from the total number of donuts to subgroups).

Figure 3 shows two handwritten mathematical abstractions. (a) Subject S1: $\rightarrow \text{kotak kecil} : m = q \cdot n + r$ and $24 = 4 \cdot 6 + 0$. (b) Subject S2: $m = qn + r$ and $24 = 4 \cdot 6 + 0$.

Figure 3. Abstraction subject S1 (a) and subject S2 (b)

Figure 4 shows two handwritten mathematical abstractions. (a) Subject S3: $3 \rightarrow \text{Besar}$, $\text{Sisa } 3 \times 12 = 36$, and $72 - 36 = 36$. (b) Subject S4: $\bullet \text{ kotak kecil} \rightarrow 24 = 4 \cdot 6 + 0$, $\bullet \text{ kotak sedang} \rightarrow 24 = 2 \cdot 9 + 6$, and $\bullet \text{ kotak besar} \rightarrow 24 = 2 \cdot 12 + 0$.

Figure 4. The abstraction process of subject S3 (a) dan subject S4 (b)

Abstraction

At the abstraction stage, all subjects filtered out irrelevant information and focused on the essential elements of the problem. Even subjects with the same cognitive style performed this process in different ways.

FI subjects (S1 and S2)

S1 uses symbolic representations such as $m = q \times n + r$, which is highly appropriate as an abstraction of the donut packaging problem. Rather than being confined to the literal context of "donuts," S1 simplifies the situation into a general mathematical form. All the information used is relevant and essential for solving the problem. S1 demonstrates excellent abstraction skills by reducing a real-world context into a logical and processable mathematical structure.

S2 uses a general equation in the form of simple algebra: $m = q \times n + r$, and arranges steps such as: $24 = 6 \times 4 + 0$; $24 = 9 \times 2 + 6$; $24 = 12 \times 2 + 0$. He focuses only on key numbers and variables, avoiding lengthy descriptions of the problem's context. The use of symbols and the generalization of formulas strongly reflect his strong abstraction skills. S2 demonstrates excellent abstraction by modeling real-world information into symbolic form and using mathematical notation to solve problems.

Figure 3 shows that S1 and S2 both use symbolic representations, indicating that both possess strong abstraction skills and show similar tendencies. However, the difference lies in how they present the abstraction: S1 emphasizes more generalizable model forms, while S2 is more explicit in applying the model to specific numerical contexts. This shows that although both have high abstraction skills, S1 is more theoretical, whereas S2 is more application-oriented in using symbolic representations.

FD subjects (S3 and S4)

S3 selects only important information, namely the total number of donuts (72), the capacity of each box (6, 9, 12), and the filling strategy. He simplifies the question without writing down all the narrative context of the question at length. However, S3 does not use abstract symbols or algebraic variables, which means he is more comfortable thinking in concrete and numerical forms. S3 shows quite good abstraction, although it is numerical in nature. He successfully filters important information and compiles it in a format that directly supports the solution.

S4 does not use symbolic variables (such as $m = qn + r$), but it expresses calculations in numerical form directly. Although it does not use algebraic notation, it is able to simplify the context of the problem into relevant numbers and mathematical operations. S4's abstraction skills are quite good, because even though it is not symbolic, it manages to focus on important data and not get caught up in the narrative context of the question.

Figure 5. Pattern recognition process in S3

Figure 4 shows that S3 and S4 both do not use symbolic variables in the abstraction process and rely more on numerical approaches. However, S3 stands out with a more systematic and efficient allocation strategy, while S4 tends to divide the problem evenly first before analyzing each part. This indicates that although both demonstrate fairly good numerical abstraction skills, S3 thinks more strategically, whereas S4 is more exploratory and experimental in simplifying the problem.

Pattern Recognition

At the pattern recognition stage, all subjects were able to identify regularities or similarities in the data. Even those with the same cognitive style showed different approaches in performing this process.

FI subjects (S1 and S2)

S1 does not explicitly write down the pattern, but uses a modulus and remainder division system (r) that demonstrates an understanding of repetitive structures (multiples). He applies a similar formula to the three types of boxes, namely: $m = q \times n + r$ for small, medium, and large boxes. This indicates the use of a consistent and repetitive problem-solving pattern. S1 demonstrates the ability to recognize patterns in the solution structure even without explicitly stating them. This reflects a strong understanding of procedural patterns.

S2 realizes that 24 donuts can be divided into small and large boxes, but there are leftovers when using medium boxes. He then moves the remaining 6 from the medium box to a small box, showing an understanding that 6 donuts can be placed in 1 small box. This illustrates the use of a logical pattern among box sizes: he recognizes the multiplicative relationships between the capacities of the boxes (6, 9, 12). S2 shows excellent pattern recognition abilities, particularly in identifying the relationship between remainders and capacities and using that insight in logical decision-making.

Based on this, both recognize patterns well, but there are differences in their approaches. The distinction lies in the method: S1 identifies patterns symbolically and procedurally through the application of general formulas, while S2 identifies patterns numerically and contextually through the management of leftover donuts across box types. In other words, S1's pattern recognition is based on algebraic structures, while S2's is based on the relationship of values and multiples among concrete units.

FD subjects (S3 and S4)

S3 identifies that $72 = 36 + 18 + 18$, which results from: 3 large boxes (3×12), 2 medium boxes (2×9), and 3 small boxes (3×6). In the bottom right, he writes the factorizations: $6 = 2 \times 3$; $9 = 3 \times 3$; $12 = 2 \times 2 \times 3$. This demonstrates numerical awareness of the interconnectedness between numbers and the pattern of prime factor multiplication. S3 has good pattern recognition ability, as seen in the identification of relationships between box sizes and the use of factorization as validation and reinforcement of understanding. This is illustrated in Figure 5.

S4 realized that dividing 24 donuts into three types of box sizes resulted in a pattern: two types of boxes (6 and 12) yielded divisions without remainders, while one type of box (9) resulted in a remainder. He also recognized that the leftover from the medium box (6 donuts) could be placed into

Donat } karena terdapat 3 jenis kotak
 $\frac{24}{3} = 24$ donat

* 24 donat diisi di kotak kecil yang muat 6 donat
 $m = qn + r$ } pada kotak kecil membutuhkan
 $24 = 4 \cdot 6 + 0$ } 4 kotak dan tidak memiliki sisa

* 24 donat diisi di kotak sedang yang muat 9 donat
 $m = qn + r$ } pada kotak sedang membutuhkan
 $24 = 2 \cdot 9 + 6$ } 2 kotak dan memiliki sisa 6 donat

* 24 donat diisi di kotak besar yang muat 12 donat
 $m = qn + r$ } pada kotak besar membutuhkan
 $24 = 2 \cdot 12 + 0$ } 2 kotak dan tidak memiliki sisa

$\Rightarrow$ Karena pada kotak sedang memiliki sisa 6, yang bisa dimasukkan pada kotak kecil maka kotak yang dibutuhkan adalah

Kotak kecil 5 kotak
 Kotak sedang 2 kotak
 Kotak besar 2 kotak } sisa 0 donat

Figure 6. The Algorithmic of subjek S2

Translate : $\frac{\text{donuts}}{3} = 24$ } Because there are 3 types of boxes
 $\frac{24}{3} = 24$ donuts

- ❖ 24 donuts filled in a small box that holds 6 donuts
 $m = qn + r$ Filling with small boxes requires 4 boxes
 $24 = 4 \cdot 6 + 0$ and leaves no remainder
- ❖ 24 donuts filled in medium box that holds 9 donuts
 $m = qn + r$ Filling with medium boxes requires 2
 $24 = 2 \cdot 9 + 6$ boxes and leaves 6 donuts remaining
- ❖ 24 donuts are filled in a large box that holds 12 donuts
 $m = qn + r$ Filling with medium boxes requires 2 boxes
 $24 = 2 \cdot 12 + 0$ with no donuts left over

$\Rightarrow$ Because the medium box has 6 leftovers that can be put in a small box, the box needed is

small box 5 boxes	}	left 0 donut
medium box 2 boxes		
large box 2 boxes		

a small box, showing an understanding of the relationship between the box sizes. S4 demonstrates good pattern recognition ability, as shown through the management of leftover donuts from one type of box to another compatible box.

Based on the above, both S3 and S4 exhibit strong pattern recognition, but with different emphases. S3 focuses on patterns through mathematical structures and number factorizations, while S4 identifies patterns through functional relationships between remainders and box capacities in a practical manner. Thus, S3 reflects analytical and theoretical pattern recognition, whereas S4 shows an applicable and context-based approach.

Algorithmic

At the algorithmic stage, all subjects were able to devise logical and systematic steps to solve the problem. However, even those with the same cognitive style showed different ways of carrying out this process.

FI subjects (S1 and S2)

S1 constructs a highly systematic sequence of steps: assigning variables, applying the division formula for each type of box, ordering the process from small to medium to large boxes, and finally presenting the results and verifying the remaining donuts. There is a consistent and executable logical flow, supported by sound decision-making—for example, when there are leftovers from the medium box, they are allocated to the small box. S1 demonstrates strong algorithmic ability, as reflected in the logical, sequential, and efficient arrangement of steps.

Figure 6 shows that S2 composes a well-structured sequence of steps: (1) testing the division using small boxes, resulting in 4 boxes with no remainder; (2) testing with medium boxes, yielding 2 boxes with 6 donuts remaining; and (3) testing with large boxes, fitting 2 boxes with no remainder. These steps are rewritten into a result-based procedure, where the remaining donuts are transferred into an additional small box. He concludes that the final configuration—5 small boxes, 2 medium boxes, 2 large boxes, with 0 donuts remaining—is neat and logical. S2 demonstrates strong algorithmic ability, as shown through the logical sequencing of steps, verification of remainders, and decision-making based on outcome conditions (i.e., using if-then logic).

Based on this, both S1 and S2 demonstrate high algorithmic abilities. However, S1 emphasizes formal and symbolic aspects in algorithm construction, while S2 focuses more on numerical application and explicit, concrete step sequences. This indicates that S1 tends to think algorithmically in an abstract and general manner, whereas S2 approaches algorithmic thinking in a practical and applied way.

FD subjects (S3 and S4)

S3 arranged the steps in logical order: (1) filling 3 large boxes, leaving 36 donuts; (2) filling 2 medium boxes, leaving 18 donuts; and (3) filling 3 small boxes, resulting in zero leftover donuts. Each step is numbered and arranged vertically, indicating a procedural flow of thinking. He also double-checks the remaining donuts after each step, showing control over the algorithmic process. S3 demonstrates excellent algorithmic skills, characterized by logical sequencing, process monitoring, and final result verification (remainder = 0).

S4 organized the process as follows: (1) dividing 72 donuts into 3 parts of 24 each, (2) calculating the number of boxes required for each size, (3) compiling the results with residual adjustments, and (4) concluding the total number of boxes and leftover donuts. The steps taken by S4 are structured and easy to follow, although not written as an explicit algorithm. S4 exhibits good algorithmic skills through a logical, consistent, and systematic workflow.

Although both subjects structure their steps clearly, S3 stands out more in terms of process control and verification at each stage, while S4 emphasizes initial segmentation and final adjustment. This suggests that S3 applies a more procedural and detailed algorithmic approach, whereas S4 tends to simplify the process into broader, more concise steps. Based on the above description, Table 2 can be created to summarize the computational thinking (CT) tendencies of each subject in solving mathematical problems.

DISCUSSION

The results show that all four subjects (S1–S4) demonstrated good decomposition skills, albeit with different approaches. The field-independent (FI) subjects, S1 and S2, tended to break down the problem in a more systematic and structured manner. S1 employed algebraic symbolism to represent the problem abstractly, while S2 adopted a more numerical strategy, yet still organized the sub-problems based on the types of boxes. These findings are in line with Suryanti & Masduki (2024), who state that students with a field-independent (FI) cognitive style are able to divide problems into logical components based on the internal structure of the problem, and tend to use analytical and individualistic approaches in mathematical problem solving. On the other hand, field-dependent (FD) subjects (S3 and S4) were also able to perform decomposition, but with a more practical and contextual strategy. S3 began from box capacities (bottom-up), while S4 started from the total

Table 2
The tendency of CT characteristics of each subject in solving Mathematical problem

Subject Name	Decomposition	Abstraction	Pattern Recognition	Algorithmic
S1	Breaks the problem into 3 logical parts based on box type, using symbolic mathematical notation.	Use algebraic variables and general models $m=qn+r$ to simplify the context.	Applies a consistent completion pattern for each box type, even if not stated explicitly.	Construct symbolic and systematic steps that are replicable.
S2	Divides the problem into possible fillings for each box type in a structured and focused manner.	Writes symbolic formulas, focuses on essential information, and excludes unnecessary narratives.	Identifies relationships between box size and donut remainders, developing an optimal strategy.	Follows a logical and structured sequence, including remainder management.
S3	Breaks down the total donuts based on box size numerically.	Avoids symbols; thinks concretely and numerically.	Relies on direct deductions from numerical relationships between box capacities.	Uses manual and sequential steps, easy to follow even without symbolic notation.
S4	Divides the donuts into 3 groups and test each box size explicitly.	Avoids symbols, focuses on real numbers and division, filters essential information.	Identifies that remainders from medium boxes can be transferred to small boxes.	Executes tracked and explicit steps, including decision-making based on remainder analysis.

distribution of donuts (top-down). This corroborates the findings Kozhevnikov et al. (2014) which explains that FD individuals are more dependent on the global context and less exploratory of the internal structure of the problem.

The FI subjects demonstrated excellent symbolic abstraction, as evidenced by their use of the general equation $m = q \times n + r$. S1, in particular, emphasized generalizable forms of the model, indicating a strong capacity for abstract reasoning. This suggests that FI students possess a high ability to model concrete information into symbolic representations, a skill that is crucial for the development of CT. Research by Fauzan et al. (2024) shows that FI students excel in abstraction and reversible thinking strategies, enabling them to formulate mathematical solutions with symbolic flexibility. In contrast, FD subjects (S3 and S4) demonstrated a preference for numerical abstraction—focusing on extracting relevant information and simplifying the problem context—but without utilizing algebraic symbolism. Their approach reflects a practical orientation toward problem solving rather than a symbolic or theoretical one. This is consistent with the findings of Zhang and Sternberg (2005) who stated that students with the FD style tend to choose concrete experience-based strategies over theoretical modeling.

In terms of pattern recognition, all subjects demonstrated good ability. FI subjects recognized patterns both procedurally and symbolically—for example, S1 applied a similar formula to all box types, while S2 identified patterns between box capacity and the remaining donuts. These findings support the research of Alvinaria et al. (2022), who found that FI students operate at a multistructural to relational level in pattern recognition and are capable of forming generalizations from numerical or symbolic representations. Meanwhile, FD subjects recognized patterns through numerical and practical approaches. S3 demonstrated a deeper understanding through factorization, while S4 intuitively recognized patterns between box sizes and leftover donuts. This suggests that

while FD students are able to recognize patterns, they tend to do so more effectively in visual or concrete contexts.

FI subjects (S1 and S2) demonstrated high algorithmic ability. S1 composed systematic steps using symbolic representations, while S2 arranged numerical steps explicitly and logically. This supports the findings of Saraswati and Putranto (2021) who stated that FI students tend to think algorithmically with a high level of planning and reflection and are capable of formulating solution strategies systematically. Meanwhile, FD subjects (S3 and S4) were also able to construct algorithms, but with a more practical approach based on real-world sequences. S3 exhibited strong process control and verification at each step, while S4 provided a more concise yet still logical sequence. These findings are consistent with Kholid et al. (2020); Nouri et al. (2020) who noted that FD students can form clear procedures when the problem context is concrete and tangible.

The S1 subject demonstrates strong potential as a prospective mathematics teacher with the ability to think computationally in a systematic manner. He could serve as a model in developing contextual problem-solving strategies based on computational thinking (CT) in the classroom. The subject exhibits a high level of CT ability, particularly in symbolic modeling and algorithmic structuring. This aligns with findings that effective CT training can enhance prospective teachers' understanding of CT concepts, problem-solving, and algorithmic thinking skills (Avcı & Deniz, 2022; Kite & and Park, 2023; Ye et al., 2023).

S2 is a subject with very high computational thinking (CT) ability and can serve as a model in developing CT modules that integrate algebraic and heuristic strategies. S2 represents a group of prospective teachers with strong symbolic modeling skills and can serve as a point of comparison to subjects who demonstrate more numerical or concrete thinking styles. S2's CT strength is particularly evident in the integration of algebra and heuristic reasoning. This highlights the importance of integrating CT into teacher education, emphasizing the development of training modules that address both theoretical and practical aspects (Kong, 2016; Sengupta et al., 2013; Yang & Lin, 2024; Yang, 2012).

S3 demonstrates compatibility with a CT approach grounded in concrete numerical activities, such as the use of manipulatives or visualization-based heuristic strategies. To strengthen symbolic abstraction skills, S3 could be trained through tasks involving mathematical modeling or introductory programming (e.g., pseudocode). This subject tends to rely on concrete numerical reasoning in CT, making them well-suited for activity-based learning strategies that emphasize hands-on and visual learning. Research indicates that programming- and engineering design-based activities can enhance CT understanding among prospective teachers (Saad & and Zainudin, 2024; Xu et al., 2022; Yun & and Crippen, 2025).

S4 can be viewed as a representative of the field-dependent cognitive style with strong computational thinking (CT) abilities. Appropriate CT learning strategies for this type of student include contextual, exploratory, and numerically concrete-based activities. S4 demonstrates that a practical, experience-based thinking style can lead to effective CT performance, even in the absence of symbolic abstraction. This subject reflects the characteristics of field-dependent learners who approach CT in an exploratory and context-driven manner. Learning strategies grounded in real-world problems and numerical reasoning have been shown to be effective in fostering CT among prospective teachers (Agbo et al., 2021; Angeli & Giannakos, 2020; Umutlu, 2022).

Prospective mathematics teachers generally exhibit two main types of cognitive styles: field-independent (FI) and field-dependent (FD). The FI cognitive style is characterized by an analytical thinking tendency, the ability to separate information from its context, and a high level of independence in formulating problem-solving strategies. In contrast, the FD style relies more on external contexts, adopts a global thinking approach, and tends to depend on concrete examples and external assistance to comprehend information (Herlina et al., 2023; Nicolaou & and Xistouri, 2011). In the context of mathematics learning, FI individuals are better able to identify essential information from problems and construct mathematical models independently, whereas FD individuals tend to perceive problems holistically without filtering for critical details.

The relationship between cognitive style and CT ability is highly significant. Research by Suryanti and Masduki (2024) shows that prospective teachers with a field-independent (FI) style tend to excel in the abstraction and algorithmic aspects of CT, as they are able to simplify problems into symbolic forms and think systematically. In contrast, prospective teachers with a field-

dependent (FD) style demonstrate stronger abilities in solving concrete, numerical, and practical problems but often face challenges with abstraction and generalization. In other words, cognitive style plays a crucial role in shaping how individuals represent problems and develop solutions using a CT approach.

The development of cognitive style-based computational thinking (CT) also faces several challenges. One of these is the continued use of uniform learning approaches that fail to accommodate individual thinking preferences, which hinders the optimal development of CT skills, particularly in field-dependent (FD) individuals (Papadopoulos, 2020). Additionally, limitations in abstract thinking and a reliance on external guidance pose further obstacles for FD students in developing independent and flexible CT (Fauzan et al., 2024; Zhang & Sternberg, 2005). Nevertheless, there remains significant potential for CT development. By designing adaptive, cognitive style-based learning modules for both field-independent (FI) and FD learners, CT development can be personalized. Prospective teachers with an FI style may benefit from symbolic activities and programming, while those with an FD style can be supported through contextual, visual, and manipulative approaches (Gadanidis, 2017b; Nouri et al., 2020). Integrating CT into mathematics teacher education curricula that take cognitive style into account is a strategic step in preparing future teachers who not only master content, but also think computationally and reflectively.

CONCLUSIONS

The results of this study confirm that cognitive styles influence students' CT, particularly in problem-solving approaches, symbolic modeling, and pattern recognition strategies. Field-independent (FI) students tend to be abstract, reflective, and analytical, whereas field-dependent (FD) students are more concrete, contextual, and numerically oriented. Prospective mathematics teachers with an FI cognitive style tend to excel in conceptual abstraction and algorithmic thinking, making them well-suited for programming-based CT development or symbolic modeling. In contrast, aspiring mathematics teachers with an FD cognitive style demonstrate strengths in practical decomposition and numerical pattern recognition, making them more compatible with visualization- and context-based CT approaches. These differences in cognitive characteristics indicate that although all four subjects successfully completed the CT tasks, the approaches they used reflected distinct thinking styles. This is important to consider when designing learning that adapts to students' cognitive styles.

Among prospective mathematics teachers with a Field-Independent (FI) cognitive style, two primary tendencies in computational thinking (CT) were identified. The first is Symbolic-Structural CT, characterized by the ability to formulate solutions symbolically, structurally, and in a generalizable manner, as well as by logical thinking using formal models. The second is Reflective-Tactical CT, which involves breaking down and formulating solutions systematically, reflectively, and numerically based on symbolic logic. Meanwhile, among prospective teachers with a Field-Dependent (FD) cognitive style, two different CT tendencies also emerged. The first is Concrete-Procedural CT, a thinking style that relies on concrete numerical calculations and a sequence of practical procedural steps to solve problems. The second is Exploratory-Conceptual CT, which involves the use of numerically based exploratory strategies to produce intuitive and easily understandable solutions.

The practical implication of this study is the importance of differentiating CT-based learning according to students' cognitive styles to enhance the effectiveness of teaching strategies. For example, FI students may benefit from algorithm-based challenges and mathematical modeling, while FD students are better suited to visual, concrete-numerical, or real-world context-based approaches.

Based on the findings of this study, it is recommended that future research develop learning instruments or Computational Thinking (CT) training modules tailored to the cognitive styles of prospective teachers. In-depth research using a mixed-method approach could be conducted to test the effectiveness of differentially designed CT-based learning strategies for individuals with both field-independent and field-dependent styles. Additionally, further studies could explore the relationship between CT and other variables such as metacognitive abilities, technology-based

problem-solving, or digital teaching competencies. Large-scale classroom trials are also necessary to ensure the generalizability of findings and the sustainability of CT implementation in mathematics teacher education

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