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COMPARING COMPUTATIONAL THINKING SKILLS AMONG GRADE 8 STUDENTS IN MATHEMATICS: A BASELINE ANALYSIS OF FOUR COMPUTATIONAL THINKING DIMENSIONS

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Abstract

Computational thinking has become an important area of research in school education because it supports students in approaching problems through systematic and logical processes. Mathematics provides an appropriate context for developing computational thinking because students regularly engage in problem solving, identifying patterns, breaking problems into smaller parts, developing procedures, and selecting relevant information. The present study examined and compared the baseline performance of Grade 8 students in four computational thinking dimensions: pattern recognition, algorithmic thinking, decomposition, and abstraction. A quantitative research approach and a one-group baseline comparative design were used. Data were collected from 60 Grade 8 students through a curriculum-embedded computational thinking test based on Mathematics content. Each computational thinking dimension was assessed through items designed to measure students' ability to recognize patterns, develop systematic procedures, decompose mathematical problems, and identify relevant information and general structures. Descriptive statistics and a one-way repeated-measures analysis of variance were used to analyze the data. The findings showed that pattern recognition had the highest mean score ($M = 4.38$, $SD = 2.27$), whereas algorithmic thinking had the lowest mean score ($M = 2.75$, $SD = 2.47$). Decomposition ($M = 3.59$, $SD = 1.87$) and abstraction ($M = 3.63$, $SD = 2.77$) were between these two dimensions. The repeated-measures ANOVA indicated a statistically significant difference among the four dimensions, $F(3, 177) = 11.36$, $p < .001$, $\eta p^2 = .161$. Bonferroni-adjusted comparisons showed significant differences between pattern recognition and algorithmic thinking, pattern recognition and decomposition, and decomposition and algorithmic thinking. The differences involving abstraction were not statistically significant after adjustment. The findings suggest that Grade 8 students did not demonstrate an equal level of performance across the four dimensions of computational thinking at

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baseline. The results provide a useful diagnostic basis for designing Mathematics instruction and future computational thinking interventions.

Introduction

Computational thinking (CT) is increasingly recognized as an important way of approaching problems systematically and developing solutions that can be represented and carried out through computational processes. Wing (2006) described computational thinking as a fundamental skill that is not limited to computer scientists. The concept includes ways of thinking that involve abstraction, decomposition, algorithmic processes, problem solving, and systematic reasoning. Since the introduction of the concept into wider educational discussion, CT has received increasing attention in school education and curriculum development.

Computational thinking is particularly relevant to Mathematics because mathematical learning involves many processes that are closely related to computational thinking. Students solve complex problems, identify relationships, recognize patterns, develop procedures, organize information, and use logical reasoning. Therefore, Mathematics classrooms can provide opportunities for students to develop CT while learning mathematical concepts. Recent reviews have shown increasing integration of computational thinking into Mathematics education, although the relationship between CT and mathematical learning is complex and different instructional approaches have been used across educational contexts (Nordby et al., 2022; Ye et al., 2023).

Computational thinking is a multidimensional construct. Different researchers have identified different skills and practices within CT, and there is no single universally accepted list of CT components. However, decomposition, pattern recognition, abstraction, and algorithmic thinking are frequently discussed in CT and mathematics education research. Decomposition involves breaking a complex problem into smaller and more manageable parts. Pattern recognition involves identifying similarities, relationships, or repeated structures. Algorithmic thinking involves developing a logical sequence of steps to solve a problem. Abstraction involves identifying important information and ignoring unnecessary details to focus on the underlying structure of a problem.

The four dimensions examined in the present study are particularly relevant to Mathematics learning. For example, a student solving a complex area problem may decompose the problem into smaller shapes. A student working with number sequences may recognize a repeated relationship or pattern. A student solving an equation may develop a sequence of logical steps. Similarly, a student solving a word problem may identify the relevant information and ignore unnecessary details. Thus, these CT dimensions can be embedded within ordinary mathematical problem-solving processes.

Previous research has increasingly examined CT within Mathematics education. Nordby et al. (2022), in a systematic review of CT in primary Mathematics classrooms, found that CT activities have been integrated with Mathematics in different ways, including activities focusing on specific CT skills such as decomposition and abstraction. Ye et al. (2023) also reported that CT and Mathematics can interact through processes in which students use mathematical reasoning to construct, interpret, and solve computational problems. These studies indicate that Mathematics is an important context for examining computational thinking.

Although research on CT in Mathematics education has increased, there remains a need to understand students' performance across individual CT dimensions. A total CT score can provide an overall indication of students' computational thinking, but it may conceal differences among particular skills. For example, students may be able to identify mathematical

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patterns but experience difficulty in developing systematic algorithms. Similarly, students may be able to solve problems involving decomposition but have difficulty identifying the most relevant information. Therefore, examining individual dimensions can provide more detailed information about students' strengths and areas that require further instructional attention.

This issue is particularly important at the elementary and middle school levels, where students are developing increasingly complex mathematical reasoning skills. A baseline assessment of individual CT dimensions can provide evidence about students' existing performance before an instructional intervention is implemented. Such information can also help researchers identify which dimensions require greater attention during instructional planning.

The present study therefore focuses on the baseline comparison of four CT dimensions among Grade 8 students in Mathematics. The study does not examine the effectiveness of an intervention. Instead, it provides a diagnostic analysis of students' initial performance in pattern recognition, algorithmic thinking, decomposition, and abstraction. This baseline information can provide a foundation for subsequent research on activity-based teaching and the development of computational thinking in Mathematics classrooms.

Problem of the Study

Computational thinking is increasingly incorporated into educational research and Mathematics instruction, but students may not develop all CT skills at the same level. Much of the existing research examines CT as an overall construct or investigates the effect of particular instructional approaches. As a result, there is a need for more detailed examination of students' performance across specific CT dimensions.

In the Pakistani school context, particularly at the elementary level, there is a need to establish students' existing level of computational thinking through Mathematics before introducing specific instructional interventions. Without baseline information, it is difficult to determine which dimensions of CT students already demonstrate and which dimensions may require greater instructional support.

The present study addresses this need by comparing four CT dimensions among Grade 8 students. The study specifically examines pattern recognition, algorithmic thinking, decomposition, and abstraction through Mathematics-based tasks. The purpose is to determine whether students demonstrate similar levels of performance across these dimensions or whether statistically significant differences exist.

Purpose of the Study

The purpose of this study was to compare the baseline performance of Grade 8 students across four computational thinking dimensions in Mathematics: pattern recognition, algorithmic thinking, decomposition, and abstraction.

Research Objective

The objective of the study was:

To compare the baseline computational thinking skills of Grade 8 students across pattern recognition, algorithmic thinking, decomposition, and abstraction in Mathematics.

Research Question

The study addressed the following research question:

Is there a statistically significant difference among Grade 8 students' baseline performance in pattern recognition, algorithmic thinking, decomposition, and abstraction in Mathematics?

Literature Review

Computational Thinking in School Education

Computational thinking (CT) is widely discussed as a problem-solving approach involving concepts and practices associated with computing. Wing (2006) introduced CT as an important analytical ability that extends beyond computer science and can be applied to problems in different areas. Later

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research emphasized that CT should be understood as a multidimensional construct rather than as programming alone. Grover and Pea (2013) reviewed the development of CT in K–12 education and identified the need to clarify CT concepts, learning outcomes, instructional approaches, and assessment. Barr and Stephenson (2011) similarly argued that CT should be integrated across the K–12 curriculum rather than restricted to computer science classrooms.

The definition of CT remains diverse across the literature. Shute et al. (2017) reviewed existing definitions and proposed a model involving skills such as decomposition, abstraction, algorithms, debugging, iteration, and generalization. Their review also emphasized that CT can be demonstrated without necessarily writing computer programs. This is important for the present study because students were assessed through Mathematics problems rather than programming tasks.

CT has also been conceptualized specifically for Mathematics and science education. Weintrop et al. (2016) proposed a taxonomy for CT in Mathematics and science classrooms that includes data practices, modeling and simulation practices, computational problem-solving practices, and systems thinking practices. Their work supports the integration of CT into disciplinary learning environments rather than treating it as an isolated computing skill. This perspective is particularly relevant to the present study because the four CT dimensions were examined through Grade 8 Mathematics content.

Computational Thinking and Mathematics Education

Mathematics provides an important context for developing and examining CT because mathematical problem solving frequently requires students to identify patterns, organize information, break complex problems into smaller components, and develop systematic procedures. Pei et al. (2018), in their study of *Lattice Land*, demonstrated connections between computational thinking practices and mathematical habits of mind. Their work showed that CT and Mathematics can overlap through practices such as decomposition, abstraction, pattern recognition, and systematic reasoning.

A systematic review by Nordby et al. (2022) examined empirical studies of CT activities in primary Mathematics classrooms. The review found that CT had been integrated into Mathematics through both skill-focused and process-oriented activities. The skill-focused activities included practices such as sequencing, decomposition, abstraction, and related computational processes. Importantly, the review found that Mathematics content was often emphasized while CT was embedded within mathematical learning rather than taught separately.

Ye et al. (2023) conducted a systematic review of CT-based Mathematics instruction and student learning across K–12 education. Their review identified decomposition, abstraction, and algorithmic thinking as important computational practices within Mathematics learning. They also discussed pattern recognition as part of the process through which students identify similarities and general structures in mathematical problems. Their review demonstrates that mathematical problem solving can provide meaningful contexts for the development and assessment of CT.

Refvik and Bjerke (2022) also examined the relationship between CT and mathematical problem solving in primary and secondary Mathematics education. Their review found evidence that CT can be included in mathematical problem-solving processes, while also identifying a need for further research concerning the relationship between CT practices and Mathematics learning.

Cui and Ng (2021) investigated the interaction between mathematical thinking and CT among students aged approximately 12 to 14 years while they solved Mathematics problems in a block-based programming environment. Their findings showed that students experienced challenges

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associated with simultaneously applying mathematical concepts and CT processes. This finding highlights the importance of considering the relationship between mathematical knowledge and CT when interpreting students' performance. Pei et al. (2018) similarly demonstrated the close relationship between CT practices and mathematical habits of mind. Their work suggests that CT does not necessarily have to be introduced through programming. Mathematical environments can provide opportunities for students to engage in computational practices while solving mathematical problems.

Pattern Recognition

Pattern recognition involves identifying similarities, regularities, and relationships within information or problems. In Mathematics, students may recognize patterns in numerical sequences, geometric arrangements, algebraic relationships, or data. Pattern recognition can support students in identifying general relationships and applying previously identified structures to new problems.

Pattern recognition has been discussed as an important component of computational thinking in Mathematics. Ye et al. (2023) described pattern recognition as a process through which students identify similarities within and between problems and use those similarities to identify general structures. Their review provides support for examining pattern recognition within mathematical CT rather than treating it as exclusively a computer science skill.

The importance of pattern recognition is also supported by empirical work involving Mathematics learners. Recent research with secondary students has examined the ways in which pattern recognition, decomposition, abstraction, and algorithmic reasoning appear during mathematical problem solving. Such studies demonstrate that these processes can occur within Mathematics tasks without requiring programming as the primary learning environment.

Algorithmic Thinking

Algorithmic thinking involves organizing a solution into a logical and ordered sequence of steps. Shute et al. (2017) identified algorithms as one of the important facets of CT and emphasized that CT involves systematic approaches to problem solving. In Mathematics, algorithmic thinking can be demonstrated when students establish procedures for solving equations, organize the steps required to solve multistage problems, or formulate a sequence of operations.

Ye et al. (2023) described algorithmic thinking as the systematic articulation of a solution through logical, ordered, and discrete steps. Their review also showed that algorithmic thinking can be developed within Mathematics activities.

Algorithmic thinking is particularly relevant to the present study because the baseline results showed that it had the lowest mean score among the four dimensions. This makes algorithmic thinking an important area for further investigation in subsequent instructional research.

Decomposition

Decomposition involves breaking a complex problem into smaller and more manageable parts. Wing (2006) identified decomposition as an important computational approach to problem solving, and later CT frameworks have continued to treat it as a central CT practice.

Decomposition has a direct relationship with Mathematics. Students may decompose a complex geometric figure into simpler shapes, separate a word problem into smaller subproblems, or divide a multistep calculation into individual stages. Ye et al. (2023) specifically identified mathematical decomposition as a process that can involve breaking numbers, shapes, or mathematical problems into smaller components.

Pei et al. (2018) also demonstrated how decomposition can operate together with mathematical reasoning in problem-solving activities. Their work provides empirical support

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for examining decomposition as part of mathematical CT.

Abstraction

Abstraction involves focusing on important information and identifying the underlying structure of a problem while ignoring unnecessary details. It is widely recognized as a fundamental component of CT. Shute et al. (2017) included abstraction among the major CT skills in their model.

In Mathematics, abstraction can occur when students identify the relevant information in a word problem, represent a real-world situation symbolically, generalize a pattern, or identify the common structure underlying several mathematical examples. Ye et al. (2023) identified abstraction as an important computational practice in Mathematics learning.

Recent research has also highlighted the complexity of defining and assessing abstraction. Oser and Standl (2025) reviewed research on teaching and assessing abstraction in K–12 CT education and found considerable variation in how abstraction has been conceptualized and measured. Their review also identified a need for clearer approaches to assessing abstraction.

This issue is relevant to the present study because abstraction did not show statistically significant differences from the other three dimensions in the pairwise analysis. The result should therefore be interpreted cautiously and not treated simply as evidence that students were stronger or weaker in abstraction.

Assessment of Computational Thinking

Assessment is a major issue in CT research because CT includes multiple skills and can be demonstrated through different forms of performance. Shute et al. (2017) noted substantial variation in how CT has been conceptualized and assessed. Tang et al. (2020), in a systematic review of empirical CT assessment studies, found considerable variation in assessment contexts, constructs, assessment types, and psychometric evidence. They also reported that many CT assessments focused on programming or computing skills.

Román-González et al. (2017) developed and examined a Computational Thinking Test designed for students in approximately Grades 5 to 10. Their findings showed relationships between CT and other cognitive abilities, including problem-solving ability. This work is particularly relevant to the present study because the participants were Grade 8 students and the assessment was intended to measure CT-related problem-solving processes.

The assessment literature therefore supports the use of performance-based tasks and the examination of individual CT components. A single total CT score may not provide sufficient information about students' specific strengths and difficulties. Dimension-level assessment can provide a more detailed picture of students' CT performance.

Research Gap

The existing literature establishes a strong conceptual and empirical relationship between CT and Mathematics. However, research has used different CT definitions, dimensions, instructional approaches, and assessment methods. Systematic reviews have identified the need for further research examining how specific CT practices operate within Mathematics learning.

There is therefore value in examining individual CT dimensions at baseline rather than relying only on an overall CT score. The present study addresses this need by comparing four dimensions—pattern recognition, algorithmic thinking, decomposition, and abstraction—among Grade 8 students using Mathematics-based tasks. The analysis provides a diagnostic description of students' initial performance before the activity-based teaching intervention examined in the broader doctoral study.

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Methodology

Research Approach

The study used a quantitative research approach. Quantitative methods were appropriate because the study aimed to measure students' performance numerically and compare their scores across four computational thinking dimensions.

Research Design

A baseline comparative design was used to examine differences among four related CT dimensions measured from the same group of students. Because each student completed tasks representing all four dimensions, a repeated-measures analytical approach was appropriate.

Participants

The participants were 60 Grade 8 students. The students completed the mathematics-based computational thinking assessment before the intervention phase of the broader doctoral study. The present article uses these baseline data to examine differences among the four CT dimensions.

Instrument

Data were collected using a Mathematics-based computational thinking test developed for Grade 8 students. The assessment focused on four dimensions: pattern recognition, algorithmic thinking, decomposition, and abstraction. The items were embedded within Mathematics content relevant to Grade 8 learning.

Each dimension was represented by a set of items, and the scores for the items representing each dimension were combined to produce a dimension score. Each dimension had a maximum possible score of 10. The instrument was designed to assess students' ability to use computational thinking processes while working with mathematical problems.

Validity

The assessment was developed with attention to the Grade 8 Mathematics curriculum and the operational definitions of the four CT dimensions. The items were designed to represent the intended CT skills within Mathematics contexts. Content and curricular alignment were considered during the development and review of the instrument.

Data Collection

The baseline computational thinking test was administered to the participating Grade 8 students before the instructional intervention. The same assessment structure was used to obtain scores for the four CT dimensions. The data were coded and entered into SPSS for statistical analysis.

Data Analysis

Descriptive statistics were calculated for each CT dimension, including the mean and standard deviation. A one-way repeated-measures analysis of variance (ANOVA) was conducted to determine whether students' mean scores differed significantly across the four CT dimensions.

Mauchly's test of sphericity was examined before interpreting the repeated-measures ANOVA. Because the assumption of sphericity was met, the sphericity-assumed results were reported. Bonferroni-adjusted pairwise comparisons were then used to identify which dimensions differed significantly from one another.

Results

Descriptive Results

The descriptive statistics showed differences in students' baseline performance across the four CT dimensions. Pattern recognition had the highest mean score ($M = 4.38$, $SD = 2.27$), followed by abstraction ($M = 3.63$, $SD = 2.77$), decomposition ($M = 3.59$, $SD = 1.87$), and algorithmic thinking ($M = 2.75$, $SD = 2.47$).

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Table 1

Descriptive Statistics for the Four Computational Thinking Dimensions at Baseline

Computational Thinking Dimension	M	SD
Pattern Recognition	4.38	2.27
Algorithmic Thinking	2.75	2.47
Decomposition	3.59	1.87
Abstraction	3.63	2.77

Note. N = 60. The maximum possible score for each dimension was 10.

The descriptive results indicate that students performed relatively better on pattern recognition than on the other dimensions. Algorithmic thinking had the lowest mean score. However, descriptive differences alone do not establish whether the differences were statistically significant. Therefore, a repeated-measures ANOVA was conducted.

Test of Sphericity

Mauchly's test was used to examine the assumption of sphericity. The result was not statistically significant, $W = .863$, $\chi^2(5) = 8.54$, $p = .129$. Therefore, the assumption of sphericity was considered satisfied, and the sphericity-assumed results were used for interpreting the repeated-measures ANOVA.

Repeated-Measures ANOVA

The repeated-measures ANOVA showed a statistically significant difference among the four computational thinking dimensions, $F(3, 177) = 11.36$, $p < .001$, $\eta p^2 = .161$.

Table 2

Repeated-Measures ANOVA Comparing the Four Computational Thinking Dimensions

Source	SS	df	MS	F	p	ηp^2
CT Dimension	79.378	3	26.459	11.362	< .001	.161
Error	412.184	177	2.329			

Note. Sphericity was assumed because Mauchly's test was nonsignificant, $W = .863$, $\chi^2(5) = 8.537$, $p = .129$.

The significant ANOVA result indicates that students' performance was not equal across the four CT dimensions. Therefore, Bonferroni-adjusted pairwise comparisons were conducted to determine the specific differences.

Pairwise Comparisons

The Bonferroni-adjusted pairwise comparisons showed three statistically significant differences. Pattern recognition scores were significantly higher than algorithmic thinking scores, with a mean difference of 1.63 points, $p < .001$. Pattern recognition was also significantly higher than decomposition, with a mean difference of 0.78 points, $p = .012$. In addition, decomposition scores were significantly higher than algorithmic thinking scores, with a mean difference of 0.84 points, $p = .006$.

No statistically significant difference was found between pattern recognition and abstraction, $p = .066$. Similarly, the difference between algorithmic thinking and abstraction was not statistically significant, $p = .055$. The difference between decomposition and abstraction was also not statistically significant, $p = 1.000$.

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Table 3

Bonferroni-Adjusted Pairwise Comparisons among Computational Thinking Dimensions

Comparison	Mean Difference	p
Pattern Recognition – Algorithmic Thinking	1.625	< .001
Pattern Recognition – Decomposition	0.783	.012
Pattern Recognition – Abstraction	0.750	.066
Decomposition – Algorithmic Thinking	0.842	.006
Abstraction – Algorithmic Thinking	0.875	.055
Abstraction – Decomposition	0.033	1.000

Note. Mean differences are based on estimated marginal means. p values were adjusted using the Bonferroni method.

Overall, the findings show that the statistically significant differences were mainly associated with algorithmic thinking, pattern recognition, and decomposition. Algorithmic thinking had a significantly lower mean than pattern recognition and decomposition. Pattern recognition also had a significantly higher mean than decomposition. Abstraction did not differ significantly from any of the other dimensions after Bonferroni adjustment.

Discussion

The present study examined whether Grade 8 students demonstrated similar levels of performance across four computational thinking dimensions in Mathematics. The results showed a statistically significant overall difference among pattern recognition, algorithmic thinking, decomposition, and abstraction. The repeated-measures ANOVA produced $F(3, 177) = 11.36$, $p < .001$, $\eta p^2 = .161$. This finding indicates that students' performance varied across the four dimensions rather than remaining at the same level.

The descriptive results showed that pattern recognition had the highest mean score ($M = 4.38$, $SD = 2.27$), whereas algorithmic thinking had the lowest mean score ($M = 2.75$, $SD = 2.47$). Decomposition ($M = 3.59$, $SD = 1.87$) and abstraction ($M = 3.63$, $SD = 2.77$) were located between these two dimensions. These findings provide evidence that students' baseline CT performance was multidimensional.

The higher performance in pattern recognition than algorithmic thinking is particularly important. Pattern recognition requires students to identify relationships and regularities, whereas algorithmic thinking requires students to organize a solution into an ordered sequence of steps. The distinction is consistent with research showing that CT includes several related but distinguishable practices rather than one homogeneous skill (Shute et al., 2017; Ye et al., 2023).

The pairwise results showed that pattern recognition was significantly higher than algorithmic thinking. Pattern recognition was also significantly higher than decomposition. In addition, decomposition was significantly higher than algorithmic thinking. These differences suggest that the significant overall effect was mainly associated with differences involving pattern recognition, decomposition, and algorithmic thinking.

The finding concerning algorithmic thinking deserves particular attention. The mean for algorithmic thinking was the lowest of the four dimensions, and its score was significantly lower than both pattern recognition and decomposition. This may indicate that students in this sample experienced greater difficulty when they were required to organize mathematical reasoning into

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explicit sequences of steps. However, the present study cannot establish why algorithmic thinking scores were lower. Possible explanations should therefore be investigated in future qualitative or instructional research rather than inferred directly from the baseline scores.

The relationship between CT and Mathematics provides an appropriate context for interpreting this result. Weintrop et al. (2016) argued that computational problem-solving practices can be embedded in Mathematics and science classrooms. Ye et al. (2023) similarly showed that algorithmic thinking can operate as part of Mathematics learning. Therefore, the lower baseline performance observed in algorithmic thinking suggests an area that may deserve explicit attention in future Mathematics instruction.

The significant difference between pattern recognition and decomposition also provides evidence of variation between CT processes. Both skills can be used during mathematical problem solving, but they involve different forms of reasoning. Decomposition requires students to break a complex task into manageable components, whereas pattern recognition requires students to identify regularities or similarities. Previous Mathematics research has demonstrated that these practices can occur during mathematical problem solving and may interact with mathematical reasoning (Pei et al., 2018; Ye et al., 2023).

The result for abstraction requires more cautious interpretation. Although abstraction had a mean score of 3.63, the differences between abstraction and pattern recognition, algorithmic thinking, and decomposition were not statistically significant after Bonferroni adjustment. Therefore, the descriptive ordering of the four means should not be interpreted as four statistically distinct performance levels.

This finding is consistent with the broader assessment literature, which indicates that CT dimensions can be difficult to define and measure consistently. Tang et al. (2020) found considerable variation in CT assessment constructs and methods, while Oser and Standl (2025) specifically identified inconsistencies in the conceptualization and assessment of abstraction.

The present findings also support the value of dimension-level CT assessment. If only an overall CT score had been calculated, the lower performance in algorithmic thinking and the differences involving decomposition and pattern recognition might have been less visible. The use of separate dimension scores therefore provided more detailed information about students' baseline performance.

The findings are also relevant to research involving Grade 8 students. Cui and Ng (2021) examined students aged approximately 12–14 years and found that students experienced challenges when mathematical problem solving and CT were integrated within a programming environment. More recent research has continued to examine how Grade 8 students coordinate mathematical problem solving and CT strategies, suggesting that the relationship between these forms of reasoning deserves attention at this educational level.

Recent research also provides evidence that CT can be examined through Mathematics problem solving without restricting assessment to programming. For example, Lehmann (2025) examined Year 8 students' use of CT skills during mathematical problem solving and reported that abstraction and decomposition were used during analysis, while algorithmic thinking and pattern recognition appeared during exploration and implementation. This provides a useful conceptual basis for interpreting the present study's finding that the four dimensions may demonstrate different patterns of performance within mathematical problem solving.

Overall, the present results should be understood as baseline evidence rather than as evidence about instructional effectiveness. The purpose was to identify whether students demonstrated similar or different levels across four CT dimensions before the intervention. The significant differences identified in the baseline data provide a useful foundation for the subsequent examination of

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activity-based teaching in the broader doctoral study.

Conclusion

The study compared four computational thinking dimensions among 60 Grade 8 students using Mathematics-based assessment tasks. The results demonstrated statistically significant differences across the four dimensions. Pattern recognition had the highest descriptive mean, whereas algorithmic thinking had the lowest. Decomposition and abstraction had intermediate mean scores.

The repeated-measures ANOVA showed a significant difference among the dimensions, $F(3, 177) = 11.36$, $p < .001$, $\eta p^2 = .161$. Bonferroni-adjusted comparisons showed significant differences between pattern recognition and algorithmic thinking, pattern recognition and decomposition, and decomposition and algorithmic thinking. No statistically significant differences were found between abstraction and the other dimensions after adjustment.

The findings demonstrate the value of examining CT as a multidimensional construct in Mathematics education. Rather than assuming that students possess all CT skills at the same level, dimension-level assessment can identify differences in students' baseline performance. The results provide a diagnostic foundation for subsequent research on activity-based teaching and the development of computational thinking through Mathematics.

Educational Implications

The results suggest that Mathematics teachers may consider providing students with opportunities to practice different CT processes rather than treating CT as a single general ability. In particular, mathematical activities can require students to identify patterns, break complex problems into smaller parts, formulate ordered procedures, and identify relevant information.

Because algorithmic thinking had the lowest mean and differed significantly from pattern recognition and decomposition, future instructional activities in the broader study may give students explicit opportunities to construct, explain, test, and revise mathematical procedures. At the same time, the results should not be interpreted as evidence that abstraction requires less attention because its differences were not statistically significant. All four dimensions remain relevant components of the study's CT framework.

The literature supports embedding CT within Mathematics rather than necessarily teaching it as a separate subject. Mathematics tasks can provide opportunities for students to demonstrate computational practices while learning curriculum content (Weintrop et al., 2016; Nordby et al., 2022; Ye et al., 2023).

Limitations

The study has several limitations. First, the sample consisted of 60 Grade 8 students; therefore, the findings should not be generalized to all Grade 8 students without considering differences in schools, regions, and educational contexts. Second, the study focused on four computational thinking dimensions and therefore did not represent every CT skill or framework used in the literature. Third, the assessment was embedded in Mathematics content, meaning that students' performance may have been influenced by their mathematical knowledge as well as their computational thinking abilities. Finally, the study examined baseline performance and therefore does not provide evidence about the effectiveness of any particular instructional intervention.

Recommendations for Future Research

Future studies may examine the development of individual CT dimensions through different instructional approaches in Mathematics classrooms. Researchers may also investigate why students demonstrate different levels of performance across CT dimensions. Qualitative studies involving student explanations, classroom observations, or think-aloud protocols could provide additional information about how

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students approach decomposition, pattern recognition, algorithmic thinking, and abstraction.

Future research may also examine whether activity-based teaching produces different effects on individual CT dimensions rather than examining only the overall CT score. Larger samples involving multiple schools and educational contexts would further strengthen the evidence regarding CT development among Grade 8 students.

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