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ANALYZING STUDENT COMPUTATIONAL THINKING ABILITY IN DATA PRESENTATION BY MATH ANXIETY AND THEIR ASPECTS

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ABSTRACT

Computational thinking is an essential skill in mathematics learning. However, many students still face difficulties in applying its aspects. This study aims to examine differences in students' computational thinking ability in the context of data presentation based on math anxiety levels and computational thinking aspects, as well as the interaction between the two. A quantitative approach with a comparative descriptive desig was employed. The research subjects were 119 seventh-grade students of SMP IT Cordova Samarinda, selected using purposive sampling. Research instruments consisted of a math anxiety questionnaire and a computational thinking test covering four aspects: decomposition, pattern recognition, algorithm, and abstraction-generalization. Data were analyzed using the General Linear Model with Two Way Repeated Measures ANOVA. The results revealed significant differences in cmputational thinking ability based on math anxiety level, with a tendency for lower computational thinking ability among students with high math anxiety. Significant differences were also found across computational thinking aspects, with decomposition scoring the highest and abstraction-generalization the lowest. Howeve, no significant interaction was found between math anxiety level and computational thinking aspects. These findings highlight the importance of instructional approaches that consider affective factors to optimize the holistic development of students' computational thinking across all aspects.

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1. INTRODUCTION

The rapid development of technology in the era of the Industrial Revolution 5.0 requires students to master 21st-century skills such as critical thinking, communication, collaboration, creativity, and innovation. One of the cognitive skills that supports the mastery of these 21st-century competencies is computational thinking, a systematic way of solving problems using computer science principles such as decomposition, pattern recognition, algorithms, abstraction, and generalization. (Grover & Pea, 2018; Wing, 2006). Computational thinking has been integrated into curricula in various countries and is being introduced in Indonesia through the Kurikulum Merdeka, particularly in mathematics education (Kuswanto et al., 2020; Weintrop et al., 2016). Mathematics aligns with the concept of computational thinking and plays an essential role in shaping students' systematic, critical, creative, analytical, logical, and active ways of thinking, making the application of computational thinking in mathematics learning highly relevant (Nasiba, 2022; Setiana, 2018). Mathematical practices such as modeling, abstraction, and algorithms are closely aligned with the main components of computational thinking: decomposition, pattern recognition, abstraction, and algorithms (Ansori, 2020; Weintrop et al., 2016). Although computational thinking has a vital role in supporting mathematics learning, research has shown that students' computational thinking ability in mathematics remains relatively low.

Studies by Jamna et al. (2022), Lestari & Roesdiana, (2023), dan Kamil et al. (2021) found that most students fell into the low category of computational thinking ability. Students with high computational thinking ability were able to meet all aspects of computational thinking such as decomposition, pattern recognition, and algorithms, while those with medium or low ability could only meet the decomposition aspect. This indicates significant differences in students' computational thinking ability levels, with only a small proportion capable of fulfilling all aspects. Based on the preliminary study conducted by the researchers in seventh-grade classes at SMP IT Cordova Samarinda, it was found that most students experienced difficulties in applying aspects of computational thinking when solving mathematical problems. This was evident in their tendency to struggle with understanding and solving word problems, especially those requiring step-by-step analysis. The majority of students had difficulty comprehending word problems because they were unable to break down the given information into simpler components.

Students in SMP IT Cordova Samarinda often felt confused about the meaning of the problems, were reluctant to read thoroughly, and preferred questions that directly addressed the core of the inquiry. This suggests that students struggled with the process of analyzing the problem systematically. Only a few students were able to break down contextual problems into smaller parts, such as identifying the known and asked information in the given questions. Consequently, students tended to avoid word problems and instead preferred questions solvable through memorized formulas or quick tricks without understanding the underlying concepts. Ideally, students should be able to identify relationships between fundamental concepts and use them to solve various mathematical problems, rather than relying solely on memorization of formulas or procedures. It was also found that the majority of students depended more on rote memorization than on understanding problem-solving steps. For example, in fraction operations, students immediately applied cross-multiplication without first grasping the concept of finding a common denominator. This shows that most students had not yet developed algorithmic thinking optimally. Instead, they preferred instant or quick approaches without deeply understanding the solution process. This indicates variation in achievement across computational thinking aspects and suggests the possibility of other influencing factors.

On the other hand, it was also found that some seventh-grade students experienced difficulties in applying concepts, especially when required to implement them in problem-solving, even though they claimed to understand the material taught. Students were able to recall concepts during classroom learning but tended to forget them when facing mathematics tests. Some students felt that they struggled to access previously learned material due to a lack of out-of-class practice or review. Some students also felt anxious during mathematics tests because they could not access their notes, leading to uncertainty about their answers. The mathematics teacher reported rarely encountering students who avoided the subject out of fear of punishment, but often observed students who lacked self-confidence and doubted their own abilities. This suggests the presence of psychological factors affecting academic performance, one of which is math anxiety (Latifah et al., 2024).

Math anxiety is the apprehension that arises when students engage with mathematics learning (Wijaya et al., 2018). Math anxiety has been proven to disrupt logical thinking processes and lower students' academic performance. Research by Aunurrahim et al. (2024) demonstrated that students with high math anxiety were unable to meet all aspects of computational thinking, those with moderate math anxiety could only achieve two aspects (decomposition and pattern recognition), while students with low math anxiety were able to fulfill all aspects of computational thinking. Similarly, Latifah et al. (2024) reported that students with low and moderate math anxiety could achieve all aspects of computational thinking, namely decomposition, abstraction, and algorithm. In contrast, students with high math anxiety failed to achieve all computational thinking aspects. Both studies indicate that the higher the students' math anxiety level, the lower their computational thinking ability. Students with low math anxiety tend to perform better across all aspects of computational thinking, whereas students with high math anxiety struggle to apply these aspects. This affirms that math anxiety significantly influences students' computational thinking ability.

However, previous studies have only compared categories of math anxiety levels with overall computational thinking scores, without investigating how each aspect of computational thinking is affected by students' math anxiety levels. Prior studies also suggested that students with high math anxiety generally have lower computational thinking ability, but did not explain in detail which aspects are most affected by math anxiety. Although the relationship between math anxiety and computational thinking has been examined, no research has specifically investigated how the interaction of math anxiety levels influences each computational thinking aspect, particularly among seventh-grade students.

This study aims to examine (1) differences in students' computational thinking ability based on math anxiety levels, (2) differences in students' computational thinking ability based on computational thinking aspects, and (3) the interaction between math anxiety levels and computational thinking aspects on students' computational thinking ability. The findings are expected to provide new insights into the development of mathematics learning strategies that simultaneously consider cognitive and affective factors.

2. METHOD

This research employed a quantitative approach with a comparative descriptive design. It involved two factors: a between-subjects factor and a within-subjects factor. The between-subjects factor was used to analyze differences in the mean scores of computational thinking ability among groups based on math anxiety levels (low, medium, high). The within-subjects factor was used to analyze differences in the mean scores of students' computational thinking ability across computational thinking aspects (decomposition, pattern recognition, algorithm, and abstraction-generalization). Since all aspects of computational thinking were measured in the same participants, the design fell under repeated measures. Therefore, the study was analyzed using a two-way Repeated Measures ANOVA to examine the effect of each between-subjects and within-subjects factor, as well as the interaction between math anxiety levels and computational thinking aspects namely, whether math anxiety levels affect each computational thinking aspect differently.

The sampling technique used was non-probability purposive sampling. There were 119 students of SMP IT Cordova Samarinda as respondents to be analyzed. Data were obtained through two instruments: a written test to measure computational thinking ability and a Likert-scale questionnaire to measure students' math anxiety levels.

The math anxiety questionnaire employed was adapted from Cooke et al. (2011), which covers four aspects: mathematical knowledge, somatic, cognitive, and attitude. These aspects served as indicators of math anxiety measured in the questionnaire grid used in this study, as presented in Table 1.

Table 1. Blueprint of Math Anxiety Questionnaire

Indicator	Sub-indicator
Mathematic Knowledge	The emergence of thoughts and/or feelings that one's mathematical ability and understanding are inadequate.
Somatic	The appearance of physical symptoms such as palpitations, nausea, dizziness as a response to math anxiety.
Cognitif	Changes or disruptions in thinking processes, such as disorganized thoughts, difficulty recalling information, or trouble concentrating when faced with mathematical tasks.
Attitude	Responses toward mathematics in the form of feelings, beliefs, or behaviors related to self-confidence or reluctance.

The computational thinking test administered to students consisted of three essay questions, each measuring four aspects of computational thinking: decomposition, pattern recognition, algorithm, and abstraction-generalization, all within the context of data presentation. The blueprint of the computational thinking test used in this study is presented in Table 2.

The instruments used in this study underwent a content validation process conducted by experts and were piloted with non-sample students. Reliability analysis showed strong results, i.e., the math anxiety questionnaire yielded a Cronbach's Alpha of 0.751 (high reliability), while the computational thinking ability test yielded a Cronbach's Alpha of 0.952 (very high reliability).

Table 2. Blueprint of Computational Thinking Test

Aspect	Indicator
Decomposition	Ability to categorize data based on certain criteria and identify relevant pieces of information according to the problem requirements.
Pattern Recognition	Ability to observe and identify trends, regularities, or relationships from the given data, and draw conclusions based on the patterns found.
Algorithm	Ability to organize solution steps sequentially and logically by applying appropriate procedures or formulas according to the problem context.
Abstraction and Generalization	Ability to identify relevant information according to the problem requirements and develop conclusions that can be applied to similar problems.

3. RESULTS AND DISCUSSION

3.1. Results

The math anxiety data were categorized into three levels: low, medium, and high. The frequency distribution of respondents based on math anxiety levels is presented in Table 3.

Table 3. Frequency Distribution of Math Anxiety Levels

Interval	Category	Frequency
$x < 55{,}4$	Low	15
$55{,}4 \leq x < 87{,}3$	Medium	88
$87{,}3 \leq x$	High	16

Based on Table 3, it was found that most seventh-grade students at SMP IT Cordova Samarinda fell into the medium category of math anxiety, with 88 students (73.95%). Therefore, it can be concluded that the math anxiety level of seventh-grade students at SMP IT Cordova Samarinda is generally moderate.

To further examine students' computational thinking ability based on the interaction between math anxiety level and computational thinking aspects, the researchers compared the average scores of students on each computational thinking aspect across the different math anxiety categories, as presented in Table 4.

Table 4. Computational Thinking Ability Based on Math Anxiety Levels and Computational Thinking Aspects

Computational Thinking Aspect	Math Anxiety Level	N	Mean
Decomposition	Low	15	9,867
	Medium	88	8,375
	High	16	7,438
Pattern Recognition	Low	15	8,067
	Medium	88	6,784
	High	16	6,063
Algorithm	Low	15	8,733

Computational Thinking Aspect	Math Anxiety Level	N	Mean
	Medium	88	6,000
	High	16	4,563
Abstraction-Generalization	Low	15	6,733
	Medium	88	4,977
	High	16	4,500

Based on Table 4, differences were found in the mean computational thinking scores across the aspects according to math anxiety categories. In general, students with low math anxiety showed the highest averages across all computational thinking aspects (decomposition, pattern recognition, algorithm, and abstraction-generalization). Conversely, students with high math anxiety tended to have the lowest averages, particularly in algorithm and abstraction-generalization. The decreasing trend from low to high math anxiety groups was consistent across all aspects of computational thinking.

Next, assumption tests were conducted, including normality, homogeneity, and sphericity tests, to ensure that the data met the basic requirements for parametric analysis. Normality test residual normality analysis was performed using the Kolmogorov-Smirnov, as presented in Table 5.

Table 5. Residual Normality Test

Computational Thinking Aspect	Kolmogorov-Smirnov	
	Statistic	***p value***
Decomposition	0,179	$< 0{,}001$
Pattern Recognition	0,123	$< 0{,}001$
Algorithm	0,079	0,069
Abstraction-Generalization	0,089	0,022

Based on Table 5, the normality analysis showed that most residuals were not normally distributed. It was found that the residual normality assumption, as tested by the Kolmogorov-Smirnov test, was satisfied only for the algorithm aspect, with a $p\ value > 0{,}05$. In contrast, the decomposition, pattern recognition, and abstraction-generalization aspects had $p\ value < 0{,}05$ on the Kolmogorov-Smirnov, indicating that the residual normality assumption was not met.

Homogeneity Test Variance homogeneity analysis was conducted using Levene's test, as shown in Table 6.

Table 6. Variance Homogeneity Test

Computational Thinking Aspect	$p\ value$
Decomposition	0,023
Pattern Recognition	0,343
Algorithm	0,072
Abstraction-Generalization	0,577

Based on Table 6, the homogeneity analysis indicated that most computational thinking aspects met the assumption of variance homogeneity ($p\ value > 0{,}05$). Only the decomposition aspect showed a $p\ value\ (0{,}023) < 0{,}05$, which means that the variance homogeneity assumption was not satisfied for the decomposition aspect.

Similar to the normality test, which was violated because the analysis results indicated that some residuals were not normally distributed, the homogeneity test also showed that certain aspects did not meet the variance homogeneity assumption. Nevertheless, the Two-Way Repeated Measures ANOVA could still be applied or continued, by leveraging the robustness of the F-test. According to Field (2017), the F-statistic is generally robust to violations of normality given a sufficiently large sample (due to the Central Limit Theorem). Regarding the homogeneity (sphericity) violation, Field (2017) instructs that the analysis can proceed by using statistically corrected degrees of freedom (such as the Greenhouse-Geisser adjustment) to ensure a valid F-ratio.

The sphericity analysis was conducted using Mauchly's Test of Sphericity, as presented in Table 7.

Table 7. Sphericity Test

Computational Thinking Ability	
p **value**	0,001
Greenhouse-Geisser ε	0,905
Huynh-Feldt ε	0,929

Based on Table 7, the sphericity test results showed a significance value ($p\ value$) of $(0{,}001) < 0{,}05$, indicating that the sphericity assumption was not met. Therefore, corrections to the degrees of freedom had to be applied to avoid misinterpretation of the F-test results. Two correction approaches were used: Greenhouse-Geisser and Huynh-Feldt. The Greenhouse-Geisser ε value was 0.905, while the Huynh-Feldt ε value was 0.929. These corrections were applied in the analysis to adjust the calculation of degrees of freedom, ensuring that the test results remained valid despite the violation of the sphericity assumption (Field, 2017).

After all assumptions were satisfied or compensated for with appropriate corrections, the analysis was conducted using the General Linear Model (GLM) with a two-way Repeated Measures ANOVA design to examine differences in computational thinking ability in terms of the interaction between math anxiety level (between-subjects) and computational thinking aspects (within-subjects).

The hypothesis testing for the math anxiety factor on computational thinking ability is presented in Table 8.

Table 8. Results of Analysis for Math Anxiety Factor

	df	F	$p\ value$
Math Anxiety Level	2	5,413	0,006
Residual	116		

Based on Table 8, the results showed an F-value of $F(2{,}116) = 5{,}413$ with a $p\ value = 0{,}006$. Since $p\ value\ (0{,}006) < 0{,}05$, the null hypothesis ($H_0$) is rejected. This indicates that there is a significant difference in computational thinking ability based on students' math anxiety levels.

To further illustrate the pattern of differences in computational thinking scores across math anxiety levels, a boxplot is presented in Figure 1.

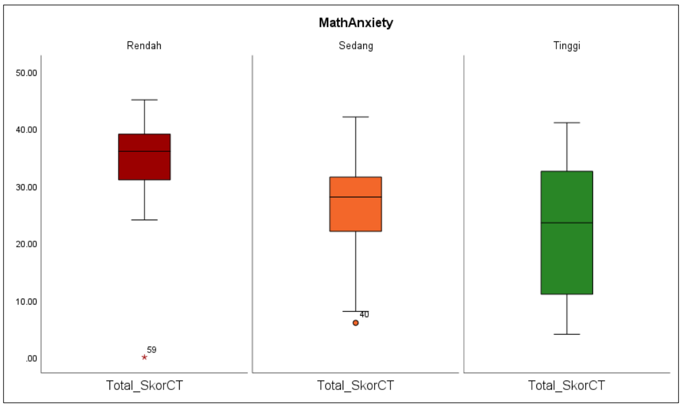

Figure 1. Boxplot of Computational Thinking Scores by Math Anxiety Level

The boxplot in Figure 1 shows that the group with low math anxiety had the highest median score in computational thinking, while the group with high math anxiety had the lowest median score. This finding suggests that the higher the math anxiety level, the lower the computational thinking ability of students.

The hypothesis testing for the computational thinking aspect factor on computational thinking ability is presented in Table 9.

Table 9. Results of Analysis for Computational Thinking Aspects

Sphericity Correction	df	F	p *value*
None	3,000	32,882	$< 0{,}001$
Greenhouse-Geisser	2,716	32,882	$< 0{,}001$

Based on the results of Mauchly's Test of Sphericity in Table 7, the sphericity assumption was violated $p\ value\ (0{,}001) < 0{,}05$. Therefore, interpretation was conducted using the Greenhouse-Geisser correction with $\varepsilon = 0{,}905$. As shown in Table 9, the analysis produced an F-value of $F(2{,}716) = 32{,}882$ with a $p\ value < 0{,}001$ after applying the Greenhouse-Geisser correction. Since $p\ value\ (0{,}001) < 0{,}05$ the null hypothesis (H_0) is rejected. This indicates that there are significant differences in computational thinking ability based on the computational thinking aspects.

To further illustrate the pattern of differences in computational thinking scores across aspects, a boxplot is presented in Figure 2.

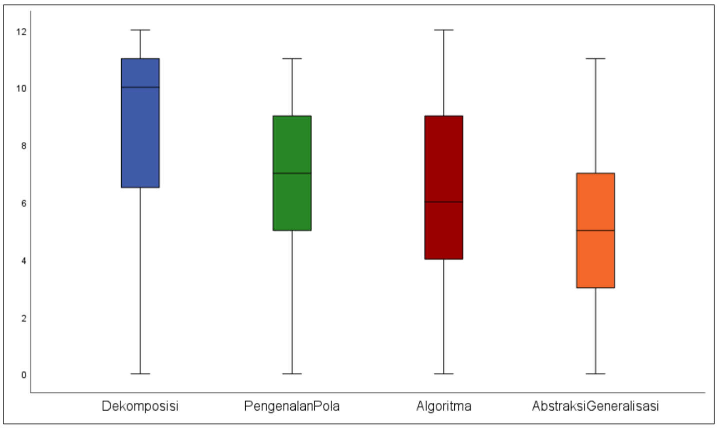

Figure 2. Boxplot of Computational Thinking Scores

by Computational Thinking Aspects

The boxplot in Figure 2 shows that the decomposition aspect had the highest median value compared to the other aspects, followed by pattern recognition and algorithm. Meanwhile, abstraction-generalization had the lowest median value. This finding suggests that most students were more proficient in decomposition, whereas they experienced greater difficulty in abstraction and generalization.

The hypothesis testing for the interaction factor between math anxiety level and computational thinking aspects on computational thinking ability is presented in Table 10.

Tabel 10. Results of Analysis for Interaction Between Math Anxiety Levels and Computational Thinking aspects

Sphericity Correction	df	F	$p\ value$
None	6,000	1,260	0,275
Greenhouse-Geisser	5,432	1,260	0,279

Based on the results of Mauchly's Test of Sphericity in Table 7, the sphericity assumption was violated with a p-value of $p\ value\ (0{,}001) < 0{,}05$. Therefore, interpretation was carried out using the Greenhouse-Geisser correction with $\varepsilon = 0{,}905$. According to Table 10, the analysis produced an F-value of $F(5{,}432) = 1{,}260$ with $p\ value = 0{,}279$ after applying the Greenhouse-Geisser correction. Since $p\ value\ (0{,}279) \geq 0{,}05$ the null hypothesis (H_0) is accepted. This means that there is no significant interaction between math anxiety levels and computational thinking aspects on students' computational thinking ability.

After the analysis using the General Linear Model (GLM) with a two-way Repeated Measures ANOVA, it was found that there were significant differences for the math anxiety factor on students' computational thinking ability. In addition, there were significant differences for the computational thinking aspect factor. However, the interaction between math anxiety levels and computational thinking aspects was not significant. Therefore, further tests were conducted separately for each main factor. Post hoc tests were performed using pairwise comparisons with Bonferroni correction.

The follow-up test for the math anxiety factor was conducted to determine the significant differences in mean computational thinking ability among the math anxiety groups. The results of the post hoc pairwise comparisons with Bonferroni correction for the math anxiety factor are presented in Table 11.

Table 11. Results of Post Hoc Analysis for Math Anxiety Factor

Math Anxiety Groups	$p\ value\ Bonferroni$
Low – Medium	0,021
Low – High	0,006
Medium – High	0,504

Based on Table 11, the results of the post hoc pairwise comparisons with Bonferroni correction show that there are significant differences between the low and medium math anxiety groups, as well as between the low and high math anxiety groups. Students with low math anxiety tended to have significantly higher computational thinking scores compared to those with medium and high math anxiety. On the other hand, no significant difference was found between the medium and high math anxiety groups.

The follow-up test for the computational thinking aspect factor was conducted to determine the significant differences in mean computational thinking ability between pairs of computational thinking aspects. The results of the post hoc pairwise comparisons with Bonferroni correction for the computational thinking aspect factor are presented in Table 12.

Table 12. Results of Post Hoc Analysis for Computational Thinking Aspects

Computational Thinking Aspect	$Mean$	df	p $value$ $Bonferroni$
Decomposition – Pattern Recognition	1,589	116	$< 0{,}001$
Decomposition – Algorithm	2,128	116	$< 0{,}001$
Decomposition – Abstraction & Generalization	3,156	116	$< 0{,}001$
Pattern Recognition – Algorithm	0,539	116	0,644
Pattern Recognition – Abstraction & Generalization	1,568	116	$< 0{,}001$
Algorithm – Abstraction & Generalization	1,028	116	$< 0{,}001$

Based on Table 12, the results of the post hoc pairwise comparisons with Bonferroni correction showed that most comparisons between computational thinking aspects were statistically significant ($p\ value < 0{,}001$), except for the comparison between pattern recognition and algorithm, which had a mean difference of only 0.539 with $p\ value = 0{,}644$. The most prominent mean difference was found between decomposition and abstraction-generalization, with the largest mean difference of 3,156 with $p\ value < 0{,}001$. Decomposition consistently had the highest mean score compared to the other aspects, while abstraction-generalization showed the lowest results.

3.2. Discussion

The results of this study revealed significant differences in students' computational thinking ability in the context of data presentation when viewed from the perspective of math anxiety levels. This finding indicates that students who felt calmer and less anxious when facing mathematics-related situations tended to have better computational thinking ability compared to those who experienced anxiety. However, significant differences only occurred between the low and medium math anxiety groups and between the low and high math anxiety groups. This suggests that computational thinking ability declines among students with medium and high math anxiety compared to those with low math anxiety. The findings imply that students' computational thinking ability decreases most noticeably when they begin to experience anxiety in mathematics-related situations. Nevertheless, once students reach the medium level of math anxiety, further increases in anxiety to the high level do not substantially decrease their computational thinking ability.

The findings of this study are consistent with the research conducted by Latifah et al. (2024), which stated that there are differences in students' computational thinking ability based on their level of math anxiety. In line with this, Aunurrahim et al. (2024) also reported that students with high math anxiety tend to have relatively low computational thinking ability. Students with medium math anxiety demonstrate moderate computational thinking ability, while students with low math anxiety show high computational thinking ability. Similarly, Amalia (2024) found that high math anxiety negatively impacts students' computational thinking ability. These findings indicate that the higher the students' math anxiety, the lower their computational thinking ability. This statement is supported by research showing that math anxiety consumes working memory resources (Ashcraft & Krause, 2007). This is critical, as computational thinking skills are heavily reliant on an individual's working memory capacity to manage and manipulate complex information. This is particularly true for tasks such as algorithm design and decomposition (Montuori et al., 2024). Math anxiety reduces self-confidence, decreases concentration, and disrupts logical and systematic thinking processes. This interference with working memory capacity is particularly detrimental as it directly affects the cognitive resources required for the development of computational thinking skills.

Thus, differences in the average computational thinking ability may be influenced by the level of math anxiety experienced by students. Therefore, efforts are needed to reduce students' math anxiety through creating an enjoyable learning atmosphere, providing gradual problem-solving exercises, and giving positive motivation to improve their self-confidence in dealing with mathematics.

In addition, the results of this study also revealed significant differences in students' computational thinking ability in the context of data presentation when viewed from the computational thinking aspects. This indicates that students' computational thinking ability varies across the different aspects of computational thinking, namely decomposition, pattern recognition, algorithm, and abstraction-generalization. In other words, students do not master all aspects of computational thinking equally. Each aspect of computational thinking requires different cognitive processes, leading to varied levels of achievement among students. However, significant differences were only found between decomposition and abstraction-generalization. This suggests that decomposition and algorithm are relatively easier aspects for students to master compared to abstraction-generalization. In other words, students are more capable of breaking down a problem into simpler sub-problems than of drawing general conclusions or forming abstractions from a given problem. These findings highlight that the cognitive characteristics of each aspect of computational thinking influence the degree of students' achievement in computational thinking.

The findings of this study are consistent with research by Abidi et al. (2023), which stated that students are more proficient in decomposition than in abstraction-generalization. Similarly, Bocconi et al. (2016) reported that students tend to find decomposition easier to master than abstraction and generalization. In line with this, Kamil et al. (2021) found that students had not yet fully achieved the abstraction-generalization aspect. This is supported by Grover & Pea (2018), who argued that elementary to middle school students show stronger understanding in decomposition, as it involves concrete reasoning that aligns with their cognitive development.

Meanwhile, according to Weintrop et al. (2016), abstraction and generalization represent higher-order thinking in computational thinking, related to conceptual transformation skills, namely the ability to develop generalizable models from specific contexts. Similarly, Shute (2017) emphasized that abstraction and generalization are higher-order thinking processes that require skills in formulating general principles from various cases or problems logically and systematically. Therefore, abstraction and generalization tend to develop more slowly in middle-aged students. Consequently, these findings reinforce the view that computational thinking instruction needs to be designed gradually, beginning with more concrete and operational aspects before directing students toward more conceptual, reflective, and abstract aspects.

In addition to students' cognitive development factors, the characteristics of the data presentation material used in this study also influenced which computational thinking aspects were more prominent. Data presentation material is generally concrete, visual, and closely related to students' everyday experiences, such as reading tables, bar graphs, or pie charts. According to Adu-Gyamfi & Bossé (2014), data presentation activities encourage students to separate information, classify data, and identify components of a visual representation, which is closely related to the decomposition process—breaking down complex information into simpler parts, such as sorting data categories, analyzing differences in frequency values of presented data, and comparing sections within a graph. This process represents the application of decomposition, as students learn to understand the overall data by first identifying its individual components.

On the other hand, Ow-Yeong et al. (2023) emphasized that abstraction and generalization focus more on the ability to construct conceptual patterns and create higher symbolic representations, which involve developing models, understanding relationships among data, and drawing conclusions based on identified patterns. In the context of data presentation, activities that demand abstraction and generalization include inferring trends from data, constructing representational models based on identified patterns, or linking the presented information to broader contexts. However, these abilities tend not to be fully developed at the junior high school level, where instruction in data presentation emphasizes visual understanding and direct interpretation of data.

Conceptually, Grover & Pea (2013) highlighted that differences in mastery of computational thinking aspects strongly depend on the type of activities and learning materials provided to students. Similarly, Yadav et al. (2014) demonstrated that task characteristics or content influence which aspects of computational thinking are more prominent than others. Therefore, the results of this study are contextual to the data presentation material. If more abstract materials such as algebra or functions were used, it is likely that aspects such as abstraction or algorithm would be more prominent. This underscores the importance of interpreting students' computational thinking abilities in relation to the context of the material used in the research measurement.

Furthermore, the results of this study also showed no interaction between math anxiety levels and computational thinking aspects in relation to students' computational thinking ability in the context of data presentation. This indicates that the influence of math anxiety on computational thinking ability does not depend on specific computational thinking aspects, and vice versa. In other words, the effects of the two factors math anxiety level and computational thinking aspects are independent and do not influence one another. These findings suggest that math anxiety affects computational thinking ability in general, rather than specific aspects. Put differently, students with high math anxiety tend to experience difficulties across all computational thinking aspects equally, rather than in a particular aspect. Conversely, students with low math anxiety consistently demonstrate better computational thinking ability across all aspects, without significant differences between them.

These findings are in line with Carey et al. (2016), who noted that math anxiety tends to affect mathematical ability as a whole, rather than showing specific interactive effects with particular cognitive aspects. Similarly, Dowker et al. (2016) revealed that the influence of math anxiety is inconsistent across cognitive aspects, but more related to general mechanisms such as working memory and emotional regulation. This statement is also supported by Wardani (2022), who asserted that math anxiety affects students' thinking processes as a whole, rather than selectively influencing specific cognitive aspects. Although there have been relatively few studies directly examining the interaction between math anxiety levels and computational thinking aspects, several previous studies have suggested that the effects of math anxiety are more comprehensive rather than concentrated on particular types of cognitive processes.

Thus, the findings of this study reinforce the theoretical foundation that math anxiety is an affective factor that negatively influences students' thinking ability, particularly in the context of computational thinking. Meanwhile, the differences in achievement across computational thinking aspects illustrate that each aspect demands distinct cognitive processes. This study provides empirical evidence that improving students' computational thinking ability requires efforts not only to reduce math anxiety but also to strengthen abstraction and generalization skills.

4. CONCLUSION

This study demonstrates that students' computational thinking ability differs significantly based on math anxiety levels and computational thinking aspects. Students with low math anxiety achieved higher levels of computational thinking compared to those with medium and high math anxiety. Differences in achievement were also found among computational thinking aspects, with decomposition being the most mastered aspect and abstraction-generalization being the weakest. No significant interaction was found between math anxiety levels and computational thinking aspects, indicating that these two factors influence computational thinking ability independently.

Mathematics learning strategies should be designed to simultaneously reduce math anxiety and develop all aspects of computational thinking in a balanced manner. Teachers are encouraged to employ contextual problem-based approaches and scaffolded practice to strengthen abstraction and generalization, while still reinforcing other aspects. Future research may explore other affective variables that could influence computational thinking and examine the effectiveness of instructional interventions specifically designed to reduce math anxiety and enhance computational thinking.

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