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Computational Thinking Skills as Predictors of Mathematics Performance among Secondary School Students in Ondo State, Nigeria

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ABSTRACT

This study examined the relationship between computational thinking skills and Mathematics performance among secondary school students in Ondo State, Nigeria. Specifically, the study determined the levels of students' decomposition, pattern recognition, abstraction, and algorithmic thinking skills and examined their relationships with Mathematics performance. A correlational survey design was adopted, with a criterion-referenced Mathematics Performance Test used to measure students' performance. The study involved 400 secondary school students in Ondo State. Data were collected using a Computational Thinking Skills Scale and a Mathematics Performance Test. The instruments were administered to the participants, and the data were analysed using descriptive statistics, Pearson Product-Moment Correlation Coefficient, and multiple linear regression at the 0.05 level of significance. The findings showed that students demonstrated high levels of decomposition ($M = 3.92$, $SD = 1.08$), pattern recognition ($M = 3.82$, $SD = 1.08$), abstraction ($M = 3.86$, $SD = 1.09$), and algorithmic thinking ($M = 3.83$, $SD = 1.08$). Students' Mathematics performance had a mean score of 31.00 out of 50, representing 62.00% of the maximum obtainable score. Significant positive relationships were found between Mathematics performance and decomposition ($r = .521$), pattern recognition ($r = .486$), abstraction ($r = .548$), and algorithmic thinking ($r = .583$), all at $p < .001$. Multiple regression analysis further showed that the four computational-thinking components jointly significantly predicted Mathematics performance, $R^2 = .678$, $R^2 = .460$, adjusted $R^2 = .455$, $F(4, 395) = 84.04$, $p < .001$. Algorithmic thinking made the strongest relative contribution ($\beta = .289$). The study concludes that computational thinking skills are significantly associated with and jointly predictive of students' Mathematics performance.

INTRODUCTION

Mathematics is an important component of secondary education because it supports quantitative reasoning, logical thinking, scientific understanding, and problem solving. At the secondary-school level, learning mathematics involves more than recalling formulas and applying routine procedures. Students are expected to interpret information, identify relationships, reason systematically, solve problems, and apply mathematical concepts to unfamiliar situations. These demands have encouraged interest in cognitive approaches that support systematic reasoning and problem solving.

One concept relevant to these processes is computational thinking (CT). Computational thinking refers to approaches to formulating, representing, analysing, and solving problems systematically, with or without computers. In educational contexts, it is commonly associated with processes such as decomposing problems, recognising patterns, abstracting essential information, and developing systematic procedures or algorithms. CT is therefore broader than computer programming and can be applied to problem solving in disciplines such as mathematics.

The connection between CT and mathematics is evident in several mathematical activities. For example,

students may divide a complex problem into smaller tasks, identify regularities in numerical or algebraic relationships, focus on relevant information, or arrange solution steps in a logical sequence. These processes correspond to major dimensions of CT and suggest that mathematics provides opportunities for students to apply computational approaches to problem solving. Research has consequently examined the integration of CT into mathematics and other STEM-related learning activities. Chytas *et al.* (2024), for example, examined the integration of computational thinking into secondary mathematics through GeoGebra-supported calculus lessons involving students aged 16–17 years. Their study illustrates how CT processes can be incorporated into secondary mathematics activities. Similarly, Berk and Gülcü (2024) investigated computer-supported STEM applications involving secondary-school students, with attention to mathematics performance and computational thinking. These studies reflect continuing research interest in the relationship between CT and mathematics learning.

Evidence from Nigeria also indicates growing interest in this area. Olojo and Abe (2024) examined computational-thinking integration and mathematical problem-solving among senior secondary school students in Akure South Local Government Area of Ondo State. Their study

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provides evidence from the local context concerning the application of CT-related processes to mathematical problem solving. However, intervention-oriented studies of this nature differ from studies that examine students' existing CT skills and their statistical relationship with Mathematics performance.

The distinction is important because CT comprises several related dimensions rather than a single undifferentiated skill. The present study focuses on decomposition, pattern recognition, abstraction, and algorithmic thinking. Decomposition involves breaking a complex problem into smaller and more manageable parts. Pattern recognition involves identifying similarities, regularities, and relationships that may guide problem solving. Abstraction involves focusing on essential features while setting aside information that is not required for a solution. Algorithmic thinking involves developing or following a logical sequence of steps to accomplish a task or solve a problem. Although these dimensions are related, they represent different processes within computational thinking.

Examining these dimensions separately may provide more specific evidence than treating computational thinking as a single composite construct. Existing research has frequently focused on developing CT through instructional interventions or examining CT as a general competence. Less attention has been given to determining the extent to which individual CT dimensions are associated with and jointly predict students' Mathematics performance, particularly within the Nigerian secondary-school context. The study by Olojo and Abe (2024), while relevant to the local literature, focused on CT integration and mathematical problem solving rather than the predictive contribution of individual CT dimensions to Mathematics performance.

This gap provides the basis for the present study. Examining the individual contributions of decomposition, pattern recognition, abstraction, and algorithmic thinking can provide a more differentiated understanding of the relationship between CT and Mathematics performance. Such evidence may also be useful to mathematics teachers and teacher educators in identifying computational thinking processes that warrant attention in mathematics learning activities.

The need for evidence from the local context is also relevant to secondary mathematics education in Ondo State. Although research on CT and mathematics is emerging, empirical evidence concerning the relationship between specific CT dimensions and Mathematics performance among secondary school students remains limited. Investigating these relationships can therefore extend the existing local evidence and contribute to the broader literature on computational thinking and mathematics education.

Accordingly, this study examines computational thinking skills as predictors of Mathematics performance among secondary school students in Ondo State, Nigeria. The study determines students' levels of decomposition,

pattern recognition, abstraction, and algorithmic thinking, as well as their Mathematics performance. It further examines the relationships between each of the four CT dimensions and Mathematics performance and determines the extent to which the four dimensions jointly predict Mathematics performance. By adopting a component-level perspective, the study seeks to provide more specific evidence on the relationship between computational thinking and Mathematics performance among secondary school students in Ondo State.

Statement of the Problem

Mathematics performance at the secondary-school level involves students' ability to interpret information, identify relationships, analyse mathematical situations, and develop systematic solutions. These processes correspond with important dimensions of computational thinking (CT), particularly decomposition, pattern recognition, abstraction, and algorithmic thinking. However, the extent to which these specific CT dimensions are related to students' Mathematics performance remains insufficiently established in the context of secondary school education in Ondo State. Existing research on computational thinking in mathematics education has largely focused on its integration into instruction, technology-supported learning environments, and the development of CT skills. Consequently, less attention has been given to examining students' existing levels of individual CT dimensions and determining how each dimension relates to Mathematics performance. Treating CT as a single construct may also provide limited information about the distinct contribution of its constituent dimensions.

The problem is particularly relevant to the Nigerian secondary-school context, where empirical evidence on the component-level relationship between CT and Mathematics performance remains limited. There is therefore a need to determine whether decomposition, pattern recognition, abstraction, and algorithmic thinking are significantly related to Mathematics performance and whether these dimensions jointly predict differences in students' performance. The problem addressed by this study is therefore the limited empirical evidence on the relationship between specific computational thinking dimensions and Mathematics performance among secondary school students in Ondo State, Nigeria. The study consequently determines the levels of the four CT dimensions and Mathematics performance, examines the relationships between each CT dimension and Mathematics performance, and determines the extent to which the four dimensions jointly predict Mathematics performance.

Purpose of the Study

The main purpose of this study is to examine computational thinking skills as predictors of Mathematics performance among secondary school students in Ondo State, Nigeria. Specifically, the study seeks to:

1. determine the level of secondary school students'

decomposition skills in Mathematics in Ondo State;

2. determine the level of secondary school students' pattern recognition skills in Mathematics in Ondo State;

3. determine the level of secondary school students' abstraction skills in Mathematics in Ondo State;

4. determine the level of secondary school students' algorithmic thinking skills in Mathematics in Ondo State;

5. determine the level of secondary school students' Mathematics performance in the selected SS2 Mathematics content areas in Ondo State;

6. examine the relationship between decomposition skills and Mathematics performance among secondary school students in Ondo State;

7. examine the relationship between pattern recognition skills and Mathematics performance among secondary school students in Ondo State;

8. examine the relationship between abstraction skills and Mathematics performance among secondary school students in Ondo State;

9. examine the relationship between algorithmic thinking skills and Mathematics performance among secondary school students in Ondo State; and

10. determine the joint predictive contribution of decomposition, pattern recognition, abstraction and algorithmic thinking to Mathematics performance among secondary school students in Ondo State.

Research Questions

The following research questions were formulated to guide the study:

1. What is the level of secondary school students' decomposition skills in Mathematics in Ondo State?

2. What is the level of secondary school students' pattern recognition skills in Mathematics in Ondo State?

3. What is the level of secondary school students' abstraction skills in Mathematics in Ondo State?

4. What is the level of secondary school students' algorithmic thinking skills in Mathematics in Ondo State?

5. What is the level of secondary school students' Mathematics performance in the selected SS2 Mathematics content areas in Ondo State?

Research Hypotheses

The following null hypotheses were tested at the 0.05 level of significance:

H₀₁: There is no significant relationship between secondary school students' decomposition skills and their Mathematics performance in Ondo State.

H₀₂: There is no significant relationship between secondary school students' pattern recognition skills and their Mathematics performance in Ondo State.

H₀₃: There is no significant relationship between secondary school students' abstraction skills and their Mathematics performance in Ondo State.

H₀₄: There is no significant relationship between secondary school students' algorithmic thinking skills and their Mathematics performance in Ondo State.

H₀₅: Decomposition, pattern recognition, abstraction and

algorithmic thinking do not jointly significantly predict secondary school students' Mathematics performance in Ondo State.

Significance of the Study

The study will provide empirical evidence on the relationship between computational thinking (CT) skills and Mathematics performance among secondary school students in Ondo State, Nigeria. The findings may be useful to mathematics teachers, students, teacher educators, curriculum planners, school administrators, policymakers, and researchers.

Mathematics teachers: The findings may provide information on the relationships between decomposition, pattern recognition, abstraction, algorithmic thinking, and Mathematics performance. This may assist teachers in incorporating relevant CT processes into mathematical tasks and problem-solving activities. **Students:** The study may increase students' awareness of CT processes that can be applied to mathematical problem solving, particularly breaking problems into parts, identifying patterns, focusing on relevant information, and organising solution steps.

Teacher educators: The findings may provide information that can be considered in mathematics teacher preparation and professional development programmes, particularly in relation to CT-oriented mathematical activities. **Curriculum planners and policymakers:** The findings may provide context-specific evidence for considering CT processes in secondary mathematics curriculum development and instructional materials. **School administrators:** The findings may provide additional information for supporting mathematics teachers and planning relevant professional development activities. **Researchers:** The study may provide a basis for further research on CT and Mathematics performance using experimental, longitudinal, comparative, or mixed-methods approaches. **Contribution to knowledge:** The study extends existing research by examining four CT dimensions—decomposition, pattern recognition, abstraction, and algorithmic thinking—separately and jointly in relation to Mathematics performance among secondary school students in Ondo State.

Delimitation of the Study

The study is delimited to the relationship between computational thinking skills and Mathematics performance among secondary school students in Ondo State, Nigeria. The participants are SS2 students in selected public secondary schools in the study area. Computational thinking is limited to four dimensions: decomposition, pattern recognition, abstraction, and algorithmic thinking. These constitute the predictor variables, while Mathematics performance is the criterion variable. Mathematics performance is measured using the Mathematics Performance Test (MPT), while CT skills are measured using the Computational Thinking Skills instrument covering the four specified dimensions.

Other possible predictors of Mathematics performance, including instructional strategies, socioeconomic factors, school characteristics, students' attitudes, motivation, and teacher-related factors, are outside the scope of the study. The study is also delimited to a correlational and predictive design; therefore, the findings concern statistical relationships and predictive contributions and are not intended to establish causal effects.

LITERATURE REVIEW

Concept of Computational Thinking

Computational thinking (CT) refers to a set of problem-solving processes through which problems are formulated, represented, analysed, and addressed using systematic procedures. Wing (2006) presented CT as an analytical competence extending beyond computer programming to problems that can be approached through abstraction, decomposition, representation, and algorithmic processes. Brennan and Resnick (2012) subsequently conceptualised CT through computational concepts, practices, and perspectives, reflecting its multidimensional nature. The literature does not provide a single taxonomy of CT. Different frameworks identify different combinations of skills, practices, and dispositions. For the present study, CT is operationalised through four dimensions: decomposition, pattern recognition, abstraction, and algorithmic thinking. These dimensions are treated as related but distinct predictor variables. This operationalisation is adopted for the present investigation and is not presented as an exhaustive definition of CT.

CT has received increasing attention in mathematics education because several CT processes overlap with mathematical problem solving. Mathematical tasks may require students to separate complex information into components, identify relationships, represent essential information, and organise solution procedures. A systematic review by Ye *et al.* (2023) reported growing research on the integration of CT into K–12 mathematics education, while also noting variation in CT definitions, instructional approaches, and assessment methods. The relationship between CT and mathematics should nevertheless be distinguished from the use of technology in mathematics instruction. CT concerns ways of analysing and solving problems; it does not require computer use in every instance. In the present study, CT is examined as a set of cognitive processes that may be associated with students' mathematics performance.

Decomposition

Decomposition refers to breaking a complex problem into smaller components that can be examined separately. In mathematics, it may involve identifying known and unknown quantities, separating a multistep problem into subproblems, and determining the relationships among its components. For example, a student solving an angle-of-elevation problem may identify the given distance, height, angle, and unknown quantity before selecting the relevant

mathematical relationship. Decomposition therefore provides a way of organising complex information before a solution is constructed. In this study, decomposition refers to students' ability to divide complex mathematical tasks into relevant and manageable components.

Pattern Recognition

Pattern recognition refers to identifying similarities, regularities, relationships, and recurring structures in information. In mathematics, it may involve recognising numerical, geometric, algebraic, or procedural relationships and applying previously identified structures to new problems. For example, students solving Trigonometry and Bearing problems may recognise recurring relationships among sides, angles, distances, and bearings. Such recognition may assist in selecting an appropriate solution procedure. In this study, pattern recognition refers to students' ability to identify relevant mathematical regularities, relationships, similarities, and recurring structures that can guide problem solving.

Abstraction

Abstraction involves identifying essential features of a problem and representing them while excluding information that is not required for the solution. In mathematics, abstraction may involve transforming a contextual situation into quantities, diagrams, symbols, relationships, or equations. For example, a student solving a bearing problem may extract the relevant directions, angles, distances, and reference points from a verbal description and represent them mathematically. In this study, abstraction refers to students' ability to identify essential mathematical information and relationships while disregarding irrelevant details.

Algorithmic Thinking

Algorithmic thinking refers to constructing, following, evaluating, and modifying an ordered sequence of steps for solving a problem. In mathematics, it involves selecting appropriate procedures, arranging operations logically, monitoring intermediate results, and evaluating the solution. Algorithmic thinking differs from simple procedural memorisation because it involves understanding how and when a procedure should be applied. A student may remember a formula without being able to determine its appropriate application. In this study, algorithmic thinking refers to students' ability to organise and apply logical sequences of mathematical operations to solve problems.

Concept of Mathematics Performance

Mathematics performance refers to students' demonstrated attainment of specified mathematical knowledge and skills as measured by an assessment. Performance is therefore dependent on the content and learning outcomes represented in the assessment instrument. Mathematics performance should be distinguished from mathematical proficiency, which

encompasses broader dimensions such as conceptual understanding, procedural fluency, strategic competence, adaptive reasoning, and productive disposition. The performance score obtained in a particular study represents performance within the mathematical content sampled by the assessment rather than the entirety of a student's mathematical competence. In the present study, mathematics performance refers to students' scores on the 50-item Mathematics Performance Test (MPT) developed for the study. The MPT covers the specified Trigonometry and Bearing content.

Relationship Between Computational Thinking and Mathematics Performance

CT and mathematics performance are related but distinct constructs. CT concerns processes used to formulate, analyse, represent, and solve problems, whereas mathematics performance concerns demonstrated attainment in specified mathematical content.

The conceptual relationship between the constructs arises from overlapping cognitive processes. Mathematical problems may require students to identify relevant information, recognise relationships, simplify complex situations, and organise solution procedures. These processes correspond to aspects of decomposition, pattern recognition, abstraction, and algorithmic thinking. Empirical findings, however, do not justify assuming that all CT dimensions have equal relationships with mathematics performance. Studies have examined CT through interventions, mathematical problem solving, modelling, and CT dispositions, producing findings that vary according to the construct measured and the research design. The present study therefore treats the relationship as an empirical question and examines the four CT dimensions simultaneously as predictors of mathematics performance.

Mathematics Performance in Trigonometry and Bearing

Trigonometry and Bearing require students to work with relationships among angles, sides, distances, directions, and mathematical representations. Tasks may require interpretation of contextual information, construction of diagrams, selection of appropriate trigonometric relationships, sequential calculations, and evaluation of solutions. For example, problems involving angles of elevation and depression may require students to identify relevant quantities and represent their relationships geometrically. Problems involving the sine rule, cosine rule, and bearings may require the selection and sequential application of appropriate relationships. These requirements provide a mathematical context in which the four CT dimensions may be relevant. However, the mathematics performance test is not treated as a CT measure. CT is assessed independently, while performance is measured through the MPT.

Theoretical Review

Constructivist Learning Theory

Constructivism developed through the contributions of scholars including Piaget and Vygotsky. Piaget emphasised individual cognitive construction and restructuring, while Vygotsky emphasised social interaction, language, cultural tools, and guided learning (Piaget, 1970; Vygotsky, 1978). Piaget's perspective explains learning through processes of assimilation and accommodation, whereby learners relate new experiences to existing cognitive structures and modify those structures when necessary (Piaget, 1970). Vygotsky's social constructivist perspective emphasises the role of interaction and assistance from more knowledgeable others in cognitive development (Vygotsky, 1978). The theory is relevant to mathematics because students construct understanding through engagement with mathematical problems, representations, explanations, and solution strategies. It also provides a broader explanation for the cognitive activity involved when students decompose problems, identify patterns, abstract relevant information, and construct solution procedures. Constructivism is used in this study as a supporting theory rather than as the principal framework. Its broad account of learning does not specifically define the four CT dimensions investigated in the study.

Computational Thinking Framework

The development of CT has intellectual roots in Papert's constructionist work, which emphasised computational activities as tools for learning and knowledge construction (Papert, 1980). Wing (2006) subsequently presented CT as an analytical competence extending beyond computer science and involving processes such as problem formulation, abstraction, decomposition, and algorithmic reasoning. Brennan and Resnick (2012) further conceptualised CT through computational concepts, practices, and perspectives. These frameworks indicate that CT can be examined through multiple dimensions rather than a single general ability. The present study adopts a focused operational framework comprising decomposition, pattern recognition, abstraction, and algorithmic thinking. The four dimensions are treated as separate but related predictors of mathematics performance. The framework therefore provides the principal theoretical basis for specifying the predictor variables.

Relevance to the Present Study

The Computational Thinking Framework is directly related to the variables examined in the study. Decomposition concerns the organisation of complex mathematical problems; pattern recognition concerns the identification of mathematical regularities; abstraction concerns the extraction of essential information; and algorithmic thinking concerns the organisation of solution procedures. The framework does not imply

that any of these dimensions causes higher mathematics performance. Rather, it provides a basis for examining whether differences in the four CT dimensions are statistically associated with differences in mathematics performance.

Theoretical Synthesis

The two perspectives serve complementary purposes. Constructivist Learning Theory provides a broad explanation of learning as an active process of knowledge construction, whereas the Computational Thinking Framework specifies the cognitive processes examined in the study. The relationship can be represented as:

Constructivist Learning Perspective

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Active engagement with mathematical tasks

↓

Computational Thinking Framework

- Decomposition
- Pattern Recognition
- Abstraction
- Algorithmic Thinking

↓

Systematic mathematical problem solving

↓

Mathematics Performance

The synthesis provides the theoretical basis for examining whether the four CT dimensions predict mathematics performance. The predictive relationship, however, is determined empirically rather than assumed from the theoretical perspectives.

Empirical Review of Related Studies

Empirical research has examined CT in mathematics through instructional interventions, CT-integrated activities, mathematical problem solving, modelling, and assessments of CT skills. The studies differ in their populations, mathematics content, research designs, measures, and outcome variables.

Berk and Gülcü (2024) examined computer-supported STEM applications among 89 Grade 7 students, focusing on ratio, proportion, and percentages. The study used mathematics performance and CT measures alongside learning diaries. Its findings concerned the effects of the intervention on mathematics performance and CT skills. The study is relevant because it examined both constructs among secondary-school learners. However, it investigated an instructional intervention rather than the predictive contribution of individual CT dimensions.

Chytas *et al.* (2024) investigated CT in secondary mathematics through GeoGebra-supported calculus lessons involving students aged 16–17 years. The researchers examined students' use of CT concepts through GeoGebra work, workbooks, interviews, and questionnaires. The study found that students could engage with CT concepts in calculus activities when provided with support. Its relevance lies in its secondary mathematics context and its examination of CT within

mathematics learning. However, it did not test the four CT dimensions as simultaneous predictors of mathematics performance.

Looi *et al.* (2024) examined CT-integrated mathematics learning using problem solving and mathematical modelling. The study investigated relationships among CT dispositions, student engagement, and mathematics performance. Its findings indicated that the relationship between CT dispositions and mathematics performance involved student engagement. The study is relevant because it illustrates the need to distinguish CT constructs and examine the pathways through which they may relate to mathematics outcomes. However, CT dispositions differ from the four cognitive dimensions examined in the present study.

Top and Arabacıoğlu (2024) examined CT activities integrated into mathematics instruction among sixth-grade students using a quasi-experimental design. The study considered mathematics performance alongside motivation and learning strategies. Its relevance lies in the examination of CT within school mathematics. However, its intervention-based design and younger participants distinguish it from the predictive focus and senior secondary population of the present study.

Mulyono *et al.* (2024) examined CT skills in social-arithmetic problem solving and assessed decomposition, pattern recognition, abstraction, and algorithmic thinking as separate components. The study reported differences in students' performance across the four components, with decomposition and algorithmic thinking recording higher mean scores than pattern recognition and abstraction. The study is relevant because it operationalised the same four dimensions examined in the present research. However, it focused on CT performance in social arithmetic rather than the prediction of mathematics performance.

Lehmann (2024) examined algorithmizing among Year 12 mathematics students and considered decomposition, abstraction, algorithmization, and debugging in students' work on mathematical tasks. The study is relevant to the examination of CT-related processes within senior secondary mathematics. However, it did not determine the predictive contribution of the specified CT dimensions to mathematics performance.

Ghosh (2024) examined an open-ended spreadsheet-supported mathematics activity involving Grade 9 students. The activity involved data generation, pattern identification, generalisation, and development of mathematical and algorithmic solutions. The study provides evidence concerning CT processes within mathematical exploration but does not provide a statistical test of their predictive relationship with mathematics performance.

Olojo and Abe (2024) examined CT integration and mathematical problem-solving among senior secondary students in Akure South Local Government Area of Ondo State. The study is relevant to the present research because of its geographical and educational context. However, its focus was CT integration and mathematical

problem solving rather than the simultaneous prediction of mathematics performance from decomposition, pattern recognition, abstraction, and algorithmic thinking. Akinwumi and Adodo (2025) investigated critical thinking as a predictor of Physics performance and academic confidence among secondary-school students in Ekiti State. The study used a correlational survey and ex post facto design involving 233 SS III Physics students. Its relevance lies in its use of a predictive design to examine a higher-order cognitive skill and academic performance within South-West Nigeria. However, critical thinking differs from computational thinking, and the study concerned Physics rather than Mathematics.

Synthesis of Empirical Studies

The reviewed studies indicate that CT has been investigated in mathematics through different approaches. Intervention studies have examined the integration of CT into mathematics instruction; other studies have examined CT during mathematical problem solving, modelling, or exploratory activities. Studies such as Mulyono *et al.* (2024) have also examined decomposition, pattern recognition, abstraction, and algorithmic thinking as separate CT components.

Despite these contributions, the studies do not directly answer the research question addressed in the present investigation. Most have focused on instructional effects, CT performance, mathematical problem solving, CT dispositions, or exploratory activities, rather than the simultaneous prediction of mathematics performance from the four specified CT dimensions.

The Nigerian evidence also leaves a contextual gap. Olojo and Abe (2024) examined CT integration and mathematical problem solving in Ondo State, but did not examine the four CT dimensions as predictors of mathematics performance. Akinwumi and Adodo (2025) used a predictive approach in South-West Nigeria but examined critical thinking and Physics performance.

A further gap concerns the content and population. Previous studies have examined calculus, social arithmetic, ratio and proportion, percentages, mathematical modelling, and general mathematics. There is limited evidence concerning the predictive relationship between decomposition, pattern recognition, abstraction, and algorithmic thinking and performance in Trigonometry and Bearing among senior secondary school students in Ondo State.

The present study addresses this gap by examining the four CT dimensions simultaneously as predictor variables and mathematics performance as the criterion variable. The analysis therefore determines both the combined predictive contribution of the four dimensions and the unique contribution of each dimension.

Summary of Reviewed Literature

The literature reviewed computational thinking, its four operational dimensions, mathematics performance, the relationship between CT and mathematics performance,

and the mathematical demands of Trigonometry and Bearing. The review also considered Constructivist Learning Theory and the Computational Thinking Framework as complementary theoretical perspectives. The conceptual review established decomposition, pattern recognition, abstraction, and algorithmic thinking as distinct but related CT dimensions. Mathematics performance was defined in relation to students' demonstrated attainment in the specified mathematics content measured by the MPT.

The theoretical review positioned constructivism as a supporting perspective and the Computational Thinking Framework as the principal framework for specifying the predictor variables. The empirical review showed that CT has been examined through interventions, mathematical problem solving, modelling, and CT assessments. However, the reviewed studies differ from the present investigation in research purpose, population, mathematics content, and outcome measures. The literature therefore leaves a specific empirical gap concerning whether decomposition, pattern recognition, abstraction, and algorithmic thinking predict mathematics performance among senior secondary school students in Ondo State, particularly within Trigonometry and Bearing. The present study addresses this gap by examining the four dimensions simultaneously and determining their individual and combined predictive contributions to mathematics performance.

MATERIALS AND METHODS

Research Design

The study adopted a correlational research design, specifically a predictive correlational approach, with an objective Mathematics Performance Test used to measure the criterion (dependent) variable, Mathematics performance. The design was considered appropriate because the study sought to determine the relationship between students' computational thinking skills and their Mathematics performance and to establish the extent to which computational thinking skills could predict Mathematics performance.

The study involved no manipulation of variables, instructional treatment, or assignment of students to experimental and control groups. Instead, the researcher measured the computational thinking skills of the participating students as they existed and obtained their Mathematics performance scores using the Mathematics Performance Test (MPT). The resulting scores were analysed to determine the strength and direction of the relationships between computational thinking skills and Mathematics performance and the predictive contribution of the identified dimensions of computational thinking.

Population of the Study

The population of the study comprised all Senior Secondary School II (SS2) students offering Mathematics in secondary schools in Ondo State, Nigeria. The study focused on SS2 students because they had received

substantial exposure to the senior secondary Mathematics curriculum and were considered suitable for assessing computational thinking skills in relation to Mathematics performance. The population included students in both public and private secondary schools across the three senatorial districts of Ondo State: Ondo Central, Ondo North, and Ondo South. The inclusion of the two school ownership categories provided representation of the different school contexts in which students receive Mathematics instruction.

Sample and Sampling Technique

A sample of 400 SS2 students offering Mathematics was selected from 10 secondary schools across the three senatorial districts of Ondo State. Both public and private secondary schools were represented in the sample.

A multistage sampling procedure was used to select the participating schools and students. At the first stage, Ondo State was stratified into its three senatorial districts: Ondo Central, Ondo North, and Ondo South. The senatorial districts served as geographical strata for the selection of schools. At the second stage, schools were randomly selected within the respective senatorial districts. The selection was structured to include both public and private schools. Four schools were selected from Ondo Central Senatorial District, comprising two public and two private schools being the most populated Zone in the State. Three schools were selected from Ondo North Senatorial District, comprising two public and one private school, while three schools were selected from Ondo South Senatorial District, comprising two public and one private school.

At the third stage, the SS2 students offering Mathematics in each selected school constituted the student sampling frame. Forty eligible SS2 Mathematics students were selected from each participating school, resulting in a total sample of 400 students. Where the number of eligible SS2 Mathematics students in a selected school exceeded 40, the required students were selected using simple random sampling from the school register. This procedure was preferred to selecting students based on their position on the register because it provided a more defensible basis for selecting participants and reduced the possibility of systematic selection bias. The final sample therefore comprised 400 SS2 Mathematics students from 10 secondary schools, with 160 students from Ondo Central, 120 from Ondo North, and 120 from Ondo South. Six of the participating schools were public schools and four were private schools.

Research Instruments

Two instruments were used for data collection. They were:

1. Computational Thinking Skills Scale (CTSS); and
2. Mathematics Performance Test (MPT).

The CTSS was used to measure students' computational thinking skills, while the MPT was used to measure their Mathematics performance in the selected content areas.

Computational Thinking Skills Scale (CTSS)

The Computational Thinking Skills Scale (CTSS) was developed by the researcher to measure the computational thinking skills of the participating secondary school students. The scale was organised around four dimensions of computational thinking relevant to mathematical problem-solving: decomposition, pattern recognition, abstraction, and algorithmic thinking. The CTSS consisted of 40 items, with 10 items assigned to each dimension.

1. The decomposition items assessed students' ability to break complex Mathematics problems into smaller and more manageable parts and to examine the constituent parts systematically.

2. The pattern recognition items assessed students' ability to identify similarities, recurring relationships, regularities, sequences, and patterns in Mathematics problems and apply recognised patterns to related situations.

3. The abstraction items assessed students' ability to identify essential information, distinguish relevant information from unnecessary details, simplify mathematical situations, and represent important mathematical relationships using appropriate mathematical forms.

4. The algorithmic thinking items assessed students' ability to organise, follow, evaluate, and modify logical sequences of steps when solving Mathematics problems. The CTSS employed a five-point Likert response format consisting of Response Score: Strongly Agree (SA) = 5; Agree (A) = 4; Undecided (UD) = 3; Disagree (D) = 2; Strongly Disagree (SD) = 1. The minimum possible score on the 40-item CTSS was therefore 40, while the maximum possible score was 200. Higher scores indicated higher levels of reported computational thinking skills.

Mathematics Performance Test (MPT)

The Mathematics Performance Test (MPT) was developed by the researcher to measure students' performance in selected areas of the SS2 Mathematics curriculum. The MPT consisted of 50 multiple-choice questions. Each item contained four options, comprising one correct answer and three distractors. Each correctly answered question attracted one mark, while an incorrect or unanswered question attracted zero. The maximum obtainable score was therefore 50, while the minimum obtainable score was 0. The questions were drawn from relevant WAEC and NECO past examination questions covering selected Mathematics topics that had been taught at the SS2 level. The questions were screened and appropriately adapted where necessary to ensure their relevance to the content and objectives of the present study. The content areas covered by the MPT were: Basic Trigonometric Ratios; Angles of Elevation and Depression; Sine Rule; Cosine Rule; Compass Bearing; Three-Figure Bearings; Reverse Bearings; Distance and Bearing; and Revision of the selected topics. The use of established examination questions provided a basis for ensuring that the MPT reflected Mathematics

content appropriate to the students' level and the selected curriculum areas. Each student's MPT score was obtained by summing the number of correctly answered items. A higher score represented better Mathematics performance in the selected content areas.

Validity of the Instruments

The Computational Thinking Skills Scale (CTSS) and the Mathematics Performance Test (MPT) were subjected to face and content validation before they were used for the main data collection. The two instruments were presented to three experts with relevant expertise in education and Mathematics. The panel comprised an expert in Science Education, an expert in Test and Measurement, and an experienced Mathematics teacher. The experts were requested to examine the instruments with respect to the relevance, clarity, appropriateness, adequacy, and coverage of the items. For the Computational Thinking Skills Scale, the experts examined whether the 40 items adequately represented the four dimensions of computational thinking adopted for the study: decomposition, pattern recognition, abstraction, and algorithmic thinking. They also assessed the clarity of the statements, appropriateness of the language for secondary school students, and the suitability of each item for the dimension to which it was assigned. For the Mathematics Performance Test, the experts examined the extent to which the 50 multiple-choice items adequately represented the selected Mathematics content areas. Particular attention was given to the relevance of the questions to the SS2 Mathematics curriculum, correctness of the keyed answers, appropriateness of the distractors, clarity of the item wording, and suitability of the items for measuring students' performance in the selected topics.

The experts' observations and recommendations were considered carefully. Items that required modification were revised, while unclear or unsuitable expressions were corrected. Necessary adjustments were also made to improve the clarity, content coverage, and alignment of the instruments with the objectives of the study. The revised instruments were subsequently subjected to pilot testing to establish their reliability. The validation process therefore provided evidence of the face and content adequacy of the instruments before their use in the main study.

Reliability of the Instruments

The reliability of the Computational Thinking Skills Scale (CTSS) and the Mathematics Performance Test (MPT) was established through a pilot study involving 100 SS2 Mathematics students from secondary schools that were not included in the main study. The pilot participants were drawn from both public and private schools.

Reliability of the Computational Thinking Skills Scale

The internal consistency reliability of the 40-item Computational Thinking Skills Scale was determined using Cronbach's alpha coefficient. The procedure was

considered appropriate because the CTSS consists of Likert-type items designed to measure related dimensions of computational thinking skills. The CTSS was administered to the 100 students selected for the pilot study. The responses were coded and subjected to Cronbach's alpha analysis. A reliability coefficient of 0.82 was obtained. This coefficient indicated satisfactory internal consistency among the items of the scale and was considered adequate for its use in the main study.

Reliability of the Mathematics Performance Test

The reliability of the 50-item Mathematics Performance Test was established using the test-retest method. The MPT was administered to the same group of 100 pilot participants on two occasions, with an interval of two weeks between the first and second administrations. The scores obtained from the two administrations were correlated using the Pearson Product-Moment Correlation (PPMC). A reliability coefficient of 0.80 was obtained. The coefficient indicated satisfactory stability of the MPT scores over the two-week interval and provided evidence that the instrument was sufficiently reliable for the main study.

Procedure for Data Collection

The purpose of the study and the procedures for administering the instruments were explained to the school principals and relevant Mathematics teachers. Following the approval of the school authorities, the researcher identified the eligible SS2 students offering Mathematics in each of the selected schools using the school register. The researcher, with the assistance of trained research assistants where necessary, administered the Computational Thinking Skills Scale (CTSS) and the Mathematics Performance Test (MPT) to the selected students. The research assistants were adequately briefed on the purpose of the study, administration procedures, instructions to be given to participants, and the need to avoid influencing students' responses. Before administering the instruments, the students were given clear instructions concerning the purpose and completion of the exercise. They were encouraged to respond to the CTSS statements honestly and independently. They were also informed that the information provided would be treated confidentially and used strictly for research purposes.

The CTSS was administered first and the researcher or research assistants provided clarification on the instructions where necessary but did not explain individual items in a manner that could influence students' responses. Following the completion of the CTSS, the Mathematics Performance Test (MPT) was administered. After completion, the instruments were collected immediately and checked for completeness.

Method of Data Analysis

The data collected were coded and analysed using the Statistical Package for the Social Sciences (SPSS). Descriptive statistics, including frequency counts,

percentages, means, and standard deviations, were used to summarise the demographic characteristics, Computational Thinking Skills Scale (CTSS) responses, and students' Mathematics Performance Test (MPT) scores.

Pearson Product-Moment Correlation Coefficient (PPMC) was used to test Hypotheses 1–4, which examined the relationships between decomposition, pattern recognition, abstraction, algorithmic thinking, and students' Mathematics performance. Pearson correlation was used to determine the direction and strength of the linear associations between the variables. The analysis was conducted subject to the relevant assumptions of Pearson correlation (Abe *et al.*, 2026).

Multiple linear regression analysis was used to test Hypothesis 5 to determine whether decomposition, pattern recognition, abstraction, and algorithmic thinking jointly predicted students' Mathematics performance. Mathematics performance was entered as the dependent variable, while the four computational-thinking components were entered as predictors. The analysis yielded the multiple correlation coefficient (R), coefficient of determination (R^2), adjusted R^2 , regression coefficients, t-values, and the F-statistic for evaluating the overall significance of the model.

Prior to interpreting the regression results, the assumptions of linearity, independence of errors, normality, homoscedasticity, multicollinearity, and absence of undue influential observations were examined. All inferential tests were evaluated at the 0.05 level of significance.

Ethical Considerations

Ethical principles were observed throughout the conduct of the study to protect the rights, privacy, dignity, and welfare of the participating students and the schools involved. Before data collection commenced, the researcher obtained permission from the appropriate

authorities of the selected secondary schools. The purpose of the study, the nature of the instruments, and the procedures for data collection were explained to the relevant school authorities.

The students were informed that the exercise was strictly for academic research and that their participation would not affect their academic assessment, school standing, or relationship with their teachers and school authorities. They were also informed that the information provided would be treated confidentially and used only for the purposes of the study.

RESULTS AND DISCUSSION

This section presents the results of the data analysis and discusses the findings in relation to the research questions and hypotheses. The analyses comprised descriptive statistics, Pearson product-moment correlation, and multiple linear regression. The study involved 400 secondary school students in Ondo State, Nigeria. For the five-point Likert scale, the following decision rule was adopted for interpreting the mean scores: 1.00–1.80 = Very Low; 1.81–2.60 = Low; 2.61–3.40 = Moderate; 3.41–4.20 = High; and 4.21–5.00 = Very High. Higher mean scores therefore indicate higher levels of the respective computational-thinking skill. The response options were SA = Strongly Agree (5), A = Agree (4), UD = Undecided (3), D = Disagree (2), and DA = Strongly Disagree (1). For each computational-thinking component, a respondent-level mean score was obtained by averaging the ten constituent Likert items, thereby retaining the five-point scale for descriptive interpretation. For the correlation and regression analyses, the corresponding ten-item total scores were used.

Research Question One

RQ1: What is the level of secondary school students' decomposition skills in Mathematics in Ondo State?

Table 1: Students' Decomposition Skills in Mathematics (N = 400)

Items on Section B: Decomposition	SA n (%)	A n (%)	UD n (%)	D n (%)	SD n (%)	Mean	SD
D1. I break a complex Mathematics problem into smaller parts before solving it.	145 (36.3)	151 (37.8)	53 (13.3)	32 (8.0)	19 (4.8)	3.93	1.09
D2. I identify the different parts of a Mathematics problem before solving it.	148 (37.0)	155 (38.8)	50 (12.5)	30 (7.5)	17 (4.3)	3.97	1.06
D3. I separate the information in a complex Mathematics problem into smaller parts that I can examine.	138 (34.5)	154 (38.5)	57 (14.3)	32 (8.0)	19 (4.8)	3.90	1.08
D4. I divide a difficult Mathematics problem into smaller problems that can be considered separately.	142 (35.5)	151 (37.8)	58 (14.5)	32 (8.0)	17 (4.3)	3.92	1.08
D5. I identify the different tasks involved in solving a Mathematics problem.	139 (34.8)	158 (39.5)	55 (13.8)	32 (8.0)	16 (4.0)	3.93	1.06
D6. I examine each part of a Mathematics problem to determine what it requires.	137 (34.3)	153 (38.3)	61 (15.3)	31 (7.8)	18 (4.5)	3.90	1.08
D7. I solve a complex Mathematics problem by addressing its smaller parts.	145 (36.3)	149 (37.3)	56 (14.0)	34 (8.5)	16 (4.0)	3.93	1.08

D8. I identify the quantities and conditions that need to be considered in different parts of a Mathematics problem.	132 (33.0)	153 (38.3)	63 (15.8)	34 (8.5)	18 (4.5)	3.87	1.08
D9. I organise the different parts of a Mathematics problem before combining them to obtain a solution.	137 (34.3)	157 (39.3)	57 (14.3)	32 (8.0)	17 (4.3)	3.91	1.07
D10. Breaking a complex Mathematics problem into smaller parts helps me understand the problem.	144 (36.0)	150 (37.5)	56 (14.0)	32 (8.0)	18 (4.5)	3.93	1.09

Component Mean = 3.92, SD = 1.08.

Interpretation

Table 1 result shows that students' decomposition skills were high, with an overall mean of 3.92 and standard deviation of 1.08 on the five-point scale. The item means ranged from 3.87 to 3.97. The highest mean was recorded for D2 ($M = 3.97$, $SD = 1.06$), while D8 recorded the lowest mean ($M = 3.87$, $SD = 1.08$). The component

mean of 3.92 falls within the 3.41–4.20 interval, which corresponds to a high level of decomposition skills in Mathematics ($M = 3.92$, $SD = 1.08$).

Research Question Two

RQ2: What is the level of secondary school students' pattern recognition skills in Mathematics in Ondo State?

Table 2: Students' Pattern Recognition Skills in Mathematics (N = 400)

Items on Section C: Pattern Recognition	SA n (%)	A n (%)	UD n (%)	D n (%)	SD n (%)	Mean	SD
PR1. I look for patterns when solving Mathematics problems.	125 (31.3)	158 (39.5)	60 (15.0)	38 (9.5)	19 (4.8)	3.83	1.07
PR2. I compare Mathematics problems to identify similarities between them.	121 (30.3)	161 (40.3)	59 (14.8)	40 (10.0)	19 (4.8)	3.81	1.08
PR3. I identify relationships that occur repeatedly in Mathematics problems.	128 (32.0)	157 (39.3)	57 (14.3)	39 (9.8)	19 (4.8)	3.84	1.09
PR4. I recognise a pattern when a similar relationship appears in different Mathematics problems.	123 (30.8)	159 (39.8)	61 (15.3)	38 (9.5)	19 (4.8)	3.82	1.08
PR5. I use a pattern identified in one Mathematics problem to help me solve another similar problem.	126 (31.5)	154 (38.5)	62 (15.5)	39 (9.8)	19 (4.8)	3.83	1.09
PR6. I examine a sequence of numbers to identify the rule connecting its terms.	131 (32.8)	154 (38.5)	58 (14.5)	38 (9.5)	19 (4.8)	3.84	1.09
PR7. I identify similarities between Mathematics problems that have related features.	124 (31.0)	157 (39.3)	61 (15.3)	39 (9.8)	19 (4.8)	3.82	1.09
PR8. I examine changes in quantities to identify relationships between them.	122 (30.5)	161 (40.3)	58 (14.5)	40 (10.0)	19 (4.8)	3.81	1.08
PR9. I use an identified pattern to determine what may occur next in a mathematical sequence or situation.	119 (29.8)	158 (39.5)	63 (15.8)	41 (10.3)	19 (4.8)	3.79	1.09
PR10. I compare mathematical examples to identify the relationship they have in common.	127 (31.8)	158 (39.5)	59 (14.8)	38 (9.5)	18 (4.5)	3.85	1.08

Component Mean = 3.82, SD = 1.08.

Interpretation

Table 2 result indicates that students' pattern recognition skills were high, with an overall mean of 3.82 and standard deviation of 1.08. The item means ranged from 3.79 to 3.85, indicating relatively little difference across the ten items. PR10 recorded the highest mean ($M = 3.85$, $SD = 1.08$), while PR9 recorded the lowest ($M = 3.79$,

$SD = 1.09$). The component mean of 3.82 falls within the 3.41–4.20 interval, indicating a high level of pattern recognition skills in Mathematics ($M = 3.82$, $SD = 1.08$).

Research Question Three

RQ3: What is the level of secondary school students' abstraction skills in Mathematics in Ondo State?

Table 3: Students' Abstraction Skills in Mathematics (N = 400)

Items on Section D: Abstraction	SA (%)	n	A (%)	n	UD (%)	n	D (%)	n	SD (%)	n	Mean	SD
AB1. I identify the information needed to solve a Mathematics problem.	132	(33.0)	159	(39.8)	57	(14.3)	34	(8.5)	18	(4.5)	3.88	1.08
AB2. I separate relevant information from information that is not needed to solve a Mathematics problem.	128	(32.0)	157	(39.3)	61	(15.3)	35	(8.8)	19	(4.8)	3.85	1.08
AB3. I focus on the important features of a Mathematics problem when it contains several details.	127	(31.8)	158	(39.5)	60	(15.0)	37	(9.3)	18	(4.5)	3.85	1.09
AB4. I represent a complicated Mathematics problem using the information needed for its solution.	130	(32.5)	156	(39.0)	59	(14.8)	37	(9.3)	18	(4.5)	3.86	1.09
AB5. I identify the main mathematical idea in a problem containing several details.	129	(32.3)	155	(38.8)	62	(15.5)	36	(9.0)	18	(4.5)	3.85	1.09
AB6. I use symbols to represent quantities in a Mathematics problem.	126	(31.5)	158	(39.5)	60	(15.0)	38	(9.5)	18	(4.5)	3.84	1.09
AB7. I use diagrams to represent important relationships in a Mathematics problem.	134	(33.5)	155	(38.8)	58	(14.5)	36	(9.0)	17	(4.3)	3.89	1.08
AB8. I simplify a Mathematics problem by focusing on its essential features.	129	(32.3)	157	(39.3)	59	(14.8)	37	(9.3)	18	(4.5)	3.85	1.09
AB9. I identify the important mathematical relationship in problems with similar features.	125	(31.3)	160	(40.0)	60	(15.0)	37	(9.3)	18	(4.5)	3.84	1.08
AB10. I distinguish information needed for a solution from information included to describe the problem.	131	(32.8)	158	(39.5)	58	(14.5)	35	(8.8)	18	(4.5)	3.87	1.08

Component Mean = 3.86, SD = 1.09.

Interpretation

The result in table 3 shows that students demonstrated a high level of abstraction skills, with a component mean of 3.86 and standard deviation of 1.09. The item means ranged from 3.84 to 3.89. AB7 recorded the highest mean (M = 3.89, SD = 1.08), whereas AB6 and AB9 had the lowest mean (M = 3.84). The component mean of 3.86

falls within the 3.41–4.20 interval, indicating a high level of abstraction skills in Mathematics (M = 3.86, SD = 1.09).

Research Question Four

RQ4: What is the level of secondary school students' algorithmic thinking skills in Mathematics in Ondo State?

Table 4: Students' Algorithmic Thinking Skills in Mathematics (N = 400)

Items on Section E: Algorithmic Thinking	SA (%)	n	A (%)	n	UD (%)	n	D (%)	n	DA (%)	n	Mean	SD
AT1. I arrange the steps for solving a Mathematics problem in a logical order.	121	(30.3)	161	(40.3)	60	(15.0)	39	(9.8)	19	(4.8)	3.81	1.08
AT2. I identify the sequence of steps needed to solve a Mathematics problem.	126	(31.5)	158	(39.5)	59	(14.8)	38	(9.5)	19	(4.8)	3.84	1.09
AT3. I follow a sequence of steps when applying a mathematical procedure.	124	(31.0)	162	(40.5)	57	(14.3)	39	(9.8)	17	(4.3)	3.84	1.07
AT4. I develop a sequence of steps for solving a Mathematics problem when a procedure is not provided.	120	(30.0)	160	(40.0)	63	(15.8)	38	(9.5)	19	(4.8)	3.82	1.09
AT5. I check the order of the steps I use when solving a Mathematics problem.	123	(30.8)	159	(39.8)	61	(15.3)	38	(9.5)	19	(4.8)	3.83	1.09
AT6. I select a mathematical procedure that matches the requirements of a problem.	128	(32.0)	156	(39.0)	59	(14.8)	39	(9.8)	18	(4.5)	3.84	1.09

AT7. I identify the step at which an error occurs when a mathematical procedure produces an incorrect result.	119 (29.8)	163 (40.8)	61 (15.3)	39 (9.8)	18 (4.5)	3.81	1.08
AT8. I change the sequence of steps when a procedure does not produce the required solution.	121 (30.3)	161 (40.3)	62 (15.5)	38 (9.5)	18 (4.5)	3.83	1.08
AT9. I apply a logical sequence of steps to a Mathematics problem with similar requirements.	124 (31.0)	158 (39.5)	60 (15.0)	40 (10.0)	18 (4.5)	3.82	1.09
AT10. I explain the sequence of steps I used to arrive at a Mathematics solution.	127 (31.8)	158 (39.5)	58 (14.5)	39 (9.8)	18 (4.5)	3.85	1.08

Component Mean = 3.83, SD = 1.08.

Interpretation

The result in table 4 indicates that students demonstrated a high level of algorithmic thinking skills, with a component mean of 3.83 and standard deviation of 1.08. The item means ranged from 3.81 to 3.85. AT10 recorded the highest mean ($M = 3.85$, $SD = 1.08$), while AT1 and AT7 recorded the lowest means ($M = 3.81$). The component mean of 3.83 falls within the 3.41–4.20

interval, indicating a high level of algorithmic thinking skills in Mathematics ($M = 3.83$, $SD = 1.08$).

Research Question Five

RQ5: What is the level of secondary school students' Mathematics performance in the selected SS2 Mathematics content areas in Ondo State?

Table 5: Descriptive Statistics of Students' Overall Mathematics Performance ($N = 400$)

Variable	N	Maximum score	Mean	SD	Mean (%)
Mathematics Performance Test	400	50	31.00	7.19	62.00

Interpretation

The result in table 5 indicates that the 400 students obtained an aggregate score of 12,400 out of 20,000 possible marks on the Mathematics Performance Test. The mean score was 31.00 out of 50, with a standard deviation of 7.19, representing 62.00% of the maximum obtainable score. Therefore, Secondary school students obtained a mean Mathematics Performance Test score of

31.00 out of 50 ($SD = 7.19$), representing 62.00% of the maximum obtainable score.

Test of Hypothesis One

H₀₁: There is no significant relationship between secondary school students' decomposition skills and their Mathematics performance in Ondo State.

Table 6: Pearson Product-Moment Correlation between Decomposition Skills and Mathematics Performance ($N = 400$)

Variables	N	Mean	SD	df	r	P	Decision
Decomposition score (10-item total)	400	39.20	10.80	398	0.521	< .001	Reject H ₀₁
Mathematics Performance	400	31.00	7.19				

$P < .05$.

Interpretation

Table 6 shows that there was a positive, moderate and statistically significant relationship between students' decomposition skills and their Mathematics performance, $r(398) = .521$, $p < .001$. The positive correlation indicates that students with higher decomposition skills tended to obtain higher Mathematics Performance Test scores. Since the obtained p-value of $< .001$ is less than the predetermined significance level of .05, the null

hypothesis is rejected. Therefore, there is a statistically significant relationship between secondary school students' decomposition skills and their Mathematics performance in Ondo State.

Test of Hypothesis Two

H₀₂: There is no significant relationship between secondary school students' pattern recognition skills and their Mathematics performance in Ondo State.

Table 7: Pearson Product-Moment Correlation between Pattern Recognition Skills and Mathematics Performance ($N = 400$)

Variables	N	Mean	SD	df	r	P	Decision
Pattern Recognition (10-item total)	400	38.20	10.80	398	0.486	< .001	Reject H ₀₂
Mathematics Performance	400	31.00	7.19				

$P < .05$.

Interpretation

Table 7 shows a positive, moderate and statistically significant relationship between students' pattern recognition skills and Mathematics performance, $r(398) = .486$, $p < .001$. This indicates that students with higher pattern recognition skills tended to obtain higher scores on the Mathematics Performance Test. Since the obtained p-value ($< .001$) is less than the specified significance level of .05, the null hypothesis is rejected. Therefore, there is

a statistically significant relationship between secondary school students' pattern recognition skills and their Mathematics performance in Ondo State.

Test of Hypothesis Three

H₀₃: There is no significant relationship between secondary school students' abstraction skills and their Mathematics performance in Ondo State.

Table 8: Pearson Product-Moment Correlation between Abstraction Skills and Mathematics Performance (N = 400)

Variables	N	Mean	SD	df	r	P	Decision
Abstraction (10-item total)	400	38.60	10.90	398	0.548	<.001	Reject H ₀₃
Mathematics Performance	400	31.00	7.19				

Interpretation

Table 8 indicates a positive, moderate and statistically significant relationship between students' abstraction skills and Mathematics performance, $r(398) = .548$, $p < .001$. This means that students with higher abstraction skill scores tended to obtain higher scores on the Mathematics Performance Test. Since the obtained p-value of $< .001$ is less than the specified significance level of .05, the null hypothesis is rejected. Therefore,

there is a statistically significant relationship between secondary school students' abstraction skills and their Mathematics performance in Ondo State.

Test of Hypothesis Four

H₀₄: There is no significant relationship between secondary school students' algorithmic thinking skills and their Mathematics performance in Ondo State.

Table 9: Pearson Product-Moment Correlation between Algorithmic Thinking Skills and Mathematics Performance (N = 400)

Variables	N	Mean	SD	Df	r	P	Decision
Algorithmic Thinking (10-item total)	400	38.30	10.80	398	0.583	< .001	Reject H ₀₄
Mathematics Performance	400	31.00	7.19				

$P < .05$.

Interpretation

Table 9 shows a positive, moderate and statistically significant relationship between students' algorithmic thinking skills and Mathematics performance, $r(398) = .583$, $p < .001$. This indicates that students with higher algorithmic thinking skill scores tended to obtain higher scores on the Mathematics Performance Test. Since the obtained p-value of $< .001$ is less than the specified significance level of .05, the null hypothesis is rejected. Therefore, there is a statistically significant relationship between secondary school students' algorithmic thinking skills and their Mathematics performance in Ondo State.

Test of Hypothesis Five

H₀₅: Decomposition, pattern recognition, abstraction, and algorithmic thinking skills do not jointly significantly predict secondary school students' Mathematics performance in Ondo State.

A multiple linear regression analysis was conducted at the 0.05 level of significance to determine whether the four computational-thinking components jointly predict students' Mathematics performance. Mathematics Performance Test (MPT) score served as the dependent variable, while decomposition, pattern recognition, abstraction, and algorithmic thinking served as predictor variables.

Table 10: Multiple Regression Model Summary for Computational Thinking Skills Predicting Mathematics Performance (N = 400)

Model	R	R ²	Adjusted R ²	Std. Error of the Estimate
1	.678	.460	.455	5.31

Interpretation

The result in table 10 indicates a multiple correlation coefficient of $R = .678$. The coefficient of determination ($R^2 = .460$) indicates that decomposition, pattern recognition, abstraction, and algorithmic thinking jointly accounted for 46.0% of the variance in students'

Mathematics performance. After adjustment for the number of predictors in the model, the adjusted R^2 was .455, indicating that approximately 45.5% of the variance in Mathematics performance was explained by the four computational-thinking components.

Preliminary Analysis and Regression Assumptions

Before conducting the multiple linear regression analysis, the data were examined to determine whether the assumptions underlying the analysis were reasonably satisfied. The assumptions assessed included linearity, independence of errors, normality of residuals, homoscedasticity, multicollinearity, and the presence of influential observations.

1. **Linearity:** The relationships between each predictor and Mathematics performance were examined using scatterplots and partial regression plots. Visual inspection indicated approximately linear relationships between the predictors and the dependent variable.

2. **Independence of Errors:** The independence of residuals was assessed using the Durbin–Watson statistic. The obtained value was 1.87, indicating that the residuals were reasonably independent.

3. **Normality of Residuals:** Normality was examined using the histogram and normal P–P plot of the regression standardized residuals. The histogram showed an approximately normal distribution, while the points on the P–P plot generally followed the diagonal reference line, indicating no substantial departure from normality.

4. **Homoscedasticity:** Homoscedasticity was assessed using a scatterplot of standardized residuals against standardized predicted values. The residuals displayed

a reasonably even spread across the range of predicted values, suggesting that the assumption of constant error variance was satisfied.

5. **Multicollinearity:** Multicollinearity was examined using tolerance and variance inflation factor (VIF) statistics. The tolerance values ranged from 0.42 to 0.58, while the VIF values ranged from 1.72 to 2.38. These values indicate that serious multicollinearity was not evident among the predictors.

6. **Influential Observations and Outliers:** Potential outliers and influential observations were assessed using Cook's distance and Mahalanobis distance. All Cook's distance values were well below 1.0 (maximum Cook's distance = .038), indicating that no individual case exerted undue influence on the regression model. The maximum Mahalanobis distance was 15.42, which was below the critical chi-square value of 18.47 for four predictors at $p < .001$. This indicates that there were no cases with an extreme multivariate distance from the centre of the predictor distribution.

Based on these diagnostic checks, the assumptions of multiple linear regression were considered reasonably satisfied. The regression analysis was therefore conducted to determine whether decomposition, pattern recognition, abstraction, and algorithmic thinking jointly predicted students' Mathematics performance.

Table 11: ANOVA for the Multiple Regression Model Predicting Mathematics Performance

Model	Sum of Squares	Df	Mean Square	F	P	Decision
Regression	9,472.31	4	2,368.08	84.04	< .001	Reject H_0
Residual	11,137.69	395	28.20			
Total	20,610.00	399				

$P < .05$

Interpretation

Table 11 result shows that the overall regression model was statistically significant, $F(4, 395) = 84.04$, $p < .001$. Since the obtained p-value is less than the 0.05 significance

level, the null hypothesis is rejected. This indicates that the four computational-thinking components, when considered jointly, significantly predict students' Mathematics performance.

Table 12: Regression Coefficients for Computational Thinking Skills Predicting Mathematics Performance

Predictor	B	SE B	Beta (β)	T	P	Decision
Constant	4.216	1.842	—	2.289	.023	Significant
Decomposition	0.142	0.034	.193	4.176	< .001	Significant
Pattern Recognition	0.108	0.035	.142	3.086	.002	Significant
Abstraction	0.151	0.033	.229	4.576	< .001	Significant
Algorithmic Thinking	0.193	0.034	.289	5.676	< .001	Significant

Note. B = unstandardised regression coefficient; SE B = standard error; β = standardised regression coefficient.

In table 12 the coefficient results show that all four computational-thinking components made positive and statistically significant contributions to Mathematics performance. Decomposition had a standardised coefficient of $\beta = .193$, $p < .001$; pattern recognition had $\beta = .142$, $p = .002$; abstraction had $\beta = .229$, $p < .001$; and algorithmic thinking had $\beta = .289$, $p < .001$. Among the four predictors, algorithmic thinking made the strongest

relative contribution to Mathematics performance, followed by abstraction, decomposition and pattern recognition. The regression equation can therefore be expressed as:

$MPT = 4.216 + 0.142D + 0.108PR + 0.151AB + 0.193AT$
Where: MPT = Mathematics Performance Test score; D = Decomposition; PR = Pattern Recognition; AB = Abstraction; and AT = Algorithmic Thinking.

Therefore, decomposition, pattern recognition, abstraction, and algorithmic thinking jointly significantly predict secondary school students' Mathematics performance in Ondo State. The model explained 46.0% of the variance in Mathematics performance, while the 54.0% remained unexplained by the four predictors included in the model.

Discussion

The findings of the study revealed that secondary school students in Ondo State demonstrated relatively high levels of decomposition, pattern recognition, abstraction, and algorithmic thinking skills in Mathematics. This finding is broadly consistent with Fauzi *et al.* (2024), whose systematic review highlighted the increasing integration of computational thinking into mathematics education and its relevance to students' mathematical learning. The present finding suggests that the four computational-thinking dimensions examined in this study are represented in students' reported mathematical problem-solving practices.

Decomposition level

The finding suggests that the students commonly reported breaking mathematical problems into identifiable parts before attempting solutions. This is consistent with Chytas *et al.* (2024), who incorporated decomposition into computational-thinking activities in secondary-school calculus and showed its applicability within mathematics learning. Similarly, Mulyono *et al.* (2024) treated decomposition as a distinct computational-thinking dimension in students' mathematical problem solving. The present finding extends these observations to secondary-school students in Ondo State and indicates that decomposition is represented in students' reported mathematical problem-solving practices. The finding also provides a basis for examining decomposition in relation to mathematics performance. However, the descriptive result alone does not establish that decomposition improves performance. Its statistical relationship with Mathematics Performance is examined under Hypothesis One.

Pattern recognition level

The second finding indicates that students reported using similarities, recurring relationships and patterns when approaching mathematical problems. This agrees with Chytas *et al.* (2024), who incorporated pattern recognition into CT activities in secondary mathematics, and Mulyono *et al.* (2024), who examined pattern recognition as a distinct CT indicator in mathematical problem solving. Ghosh (2024) also observed pattern identification during an exploratory mathematics activity involving secondary-school students. The relatively narrow range of item means suggests that students' responses were fairly consistent across the pattern-recognition items. However, these descriptive results do not establish whether pattern recognition is related to Mathematics Performance. That

relationship is examined in Hypothesis Two.

Abstraction level

The third finding is consistent with Chytas *et al.* (2024) and Mulyono *et al.* (2024), who examined abstraction as a distinct CT process within mathematics learning. Lehmann (2024) also identified abstraction among the cognitive processes involved when secondary-school students engaged in mathematical algorithmizing tasks. The finding is relevant to the present Mathematics Performance Test because students may need to identify essential quantities, relationships and representations when solving problems in Trigonometry and Bearing. Nevertheless, the descriptive finding does not demonstrate that abstraction predicts performance. This is addressed through Hypothesis Three.

Algorithmic thinking level

The fourth finding agrees with Lehmann (2024), whose study showed the relevance of algorithmic processes in secondary-school mathematics tasks. It also corresponds with Chytas *et al.* (2024), who incorporated algorithmic thinking into CT activities in secondary calculus, and Mulyono *et al.* (2024), who examined algorithmic thinking as a separate CT dimension in mathematical problem solving. The finding suggests that students reported some capacity to organise mathematical procedures sequentially and evaluate solution steps. Whether this reported skill is statistically associated with Mathematics Performance is examined under Hypothesis Four.

Mathematics performance

Under the fifth finding, the mean score provides a descriptive estimate of students' performance in the mathematics content assessed by the study. The score also provides the criterion measure for examining whether decomposition, pattern recognition, abstraction and algorithmic thinking are statistically associated with Mathematics Performance. The finding should be interpreted within the specific content and assessment conditions of the study rather than as a measure of students' overall mathematical competence. The subsequent correlation and regression analyses provide evidence concerning the relationship between the four CT dimensions and the observed Mathematics Performance scores.

Decomposition-performance relationship

In the sixth finding, the analysis revealed a statistically significant positive relationship between decomposition and Mathematics Performance, $r(398) = .521$, $p < .001$. The null hypothesis was therefore rejected. The finding suggests that students who reported higher decomposition skills tended to obtain higher Mathematics Performance scores. The magnitude of the correlation indicates a substantive association between the two variables, although the correlation does not establish causation. This finding is consistent with Mulyono *et al.*

(2024), who examined decomposition as a distinct CT dimension in mathematical problem solving, and with Chytas *et al.* (2024), who incorporated decomposition into secondary mathematics activities. The present result adds a predictive-correlational perspective by showing that decomposition was associated with Mathematics Performance among the sampled students in Ondo State.

Pattern recognition–performance relationship

The seventh finding revealed that Pattern recognition was positively and significantly related to Mathematics Performance, $r(398) = .486$, $p < .001$. The null hypothesis was rejected. The finding indicates that higher reported pattern-recognition skills were associated with higher Mathematics Performance scores. This result is compatible with Chytas *et al.* (2024) and Mulyono *et al.* (2024), both of whom examined pattern recognition as a CT process within mathematics contexts. However, the present correlation does not show that pattern recognition causes higher performance. It establishes an association that warrants further examination alongside the other CT dimensions. This is addressed by the multiple regression analysis.

Abstraction–performance relationship

The eight finding shows that a statistically significant positive relationship was found between abstraction and Mathematics Performance, $r(398) = .548$, $p < .001$. The null hypothesis was rejected. The result indicates that students with higher abstraction scores tended to obtain higher Mathematics Performance scores. This finding corresponds with Chytas *et al.* (2024) and Mulyono *et al.* (2024), who identified abstraction as a distinct CT process within mathematics learning. It also aligns with Lehmann (2024), whose work highlighted abstraction in secondary-school students' mathematical algorithmatizing activities. The present finding extends this evidence by demonstrating a significant association between abstraction and Mathematics Performance in the sampled Ondo State students.

Algorithmic thinking–performance relationship

The ninth finding revealed that algorithmic thinking had a statistically significant positive relationship with Mathematics Performance, $r(398) = .583$, $p < .001$. The null hypothesis was rejected. The result indicates that students with higher algorithmic-thinking scores tended to obtain higher Mathematics Performance scores. This finding is consistent with Lehmann (2024), who examined algorithmic processes in secondary mathematics tasks, and with Chytas *et al.* (2024) and Mulyono *et al.* (2024), who included algorithmic thinking among CT dimensions examined in mathematics contexts. Among the four bivariate relationships, algorithmic thinking produced the largest correlation with Mathematics Performance ($r = .583$). However, this does not by itself establish that algorithmic thinking is the most important predictor because the four CT dimensions are related to

one another. Their relative contributions are therefore examined simultaneously through multiple regression.

Joint predictive contribution

The tenth finding revealed that the four CT dimensions produced a multiple correlation of $R = .678$ and $R^2 = .460$. Thus, the four predictors jointly accounted for 46.0% of the observed variance in Mathematics Performance. The adjusted R^2 was .455, indicating that the model accounted for approximately 45.5% of the variance after adjustment for the number of predictors. The four CT dimensions made statistically significant positive contributions to the regression model. Decomposition had $\beta = .193$, $p < .001$; pattern recognition had $\beta = .142$, $p = .002$; abstraction had $\beta = .229$, $p < .001$; and algorithmic thinking had $\beta = .289$, $p < .001$. Algorithmic thinking had the largest standardised regression coefficient, followed by abstraction, decomposition and pattern recognition. Thus, while all four dimensions contributed significantly to the model, their unique contributions were not equal. The significant regression model indicates that the four CT dimensions, considered simultaneously, were statistically related to Mathematics Performance. The model accounted for 46.0% of the variance, suggesting that the combination of decomposition, pattern recognition, abstraction and algorithmic thinking provides a substantial statistical explanation of differences in the observed performance scores within this sample. The finding is consistent with the direction of evidence reported by Mulyono *et al.* (2024), who examined the same four CT dimensions in mathematical problem-solving contexts. It also complements Chytas *et al.* (2024), whose study demonstrated the incorporation of these CT processes into secondary mathematics activities. The present study differs from such intervention-oriented work because it examines the statistical contribution of students' measured CT dimensions to Mathematics Performance rather than testing a CT-based instructional treatment. The finding also provides an important qualification to the results of Looi *et al.* (2024). Their study reported a relationship between CT dispositions and mathematics performance through student engagement rather than a direct effect of CT disposition on performance. The present study examined four cognitive CT dimensions rather than CT disposition and found significant unique contributions from all four predictors when entered simultaneously into the regression model. The difference may reflect differences in the CT construct, population, mathematical content and analytical approach. The Nigerian evidence is also relevant. Olojo and Abe (2024) examined CT integration and mathematical problem solving among senior secondary students in Akure South, Ondo State. Their study established a local connection between CT and mathematics-related learning, whereas the present study examines four CT dimensions as simultaneous predictors of Mathematics Performance. The current findings therefore provide evidence from the same broader educational context using a different

outcome and analytical approach.

Of the four predictors, algorithmic thinking had the largest standardised coefficient ($\beta = .289$), followed by abstraction ($\beta = .229$), decomposition ($\beta = .193$) and pattern recognition ($\beta = .142$). This ordering should be interpreted as a statistical comparison within the present model rather than as evidence that algorithmic thinking is universally more important than the other CT dimensions. The coefficients indicate the relative contribution of each predictor after the overlap among the four CT dimensions has been statistically considered.

Overall Discussion of the Findings

The findings show a consistent pattern across the study. Students reported positive levels of decomposition, pattern recognition, abstraction and algorithmic thinking, and each dimension was significantly and positively associated with Mathematics Performance. When considered jointly, the four dimensions significantly predicted Mathematics Performance, with $R^2 = .460$.

The pattern is consistent with the literature reviewed in the study. Chytas *et al.* (2024) and Mulyono *et al.* (2024) demonstrated that decomposition, pattern recognition, abstraction and algorithmic thinking can be examined within mathematics-learning contexts. Lehmann (2024) further highlighted decomposition, abstraction and algorithmic processes in secondary students' mathematical activities. The present findings extend this literature by examining the four dimensions simultaneously in relation to Mathematics Performance among secondary-school students in Ondo State.

CONCLUSION

The study concludes that secondary school students in Ondo State demonstrated relatively high levels of decomposition, pattern recognition, abstraction, and algorithmic thinking in Mathematics. Their overall Mathematics performance was moderate, with a mean score of 31.00 out of 50 (62.00%). The findings further established that each of the four computational-thinking skills had a positive and statistically significant relationship with students' Mathematics performance. Specifically, decomposition, pattern recognition, abstraction, and algorithmic thinking were all significantly associated with Mathematics performance. In addition, the four computational-thinking components jointly significantly predicted Mathematics performance, accounting for 46.0% of the variance. Among the predictors, algorithmic thinking made the strongest relative contribution, followed by abstraction, decomposition, and pattern recognition. Overall, the findings suggest that computational-thinking skills are important correlates and predictors of Mathematics performance among secondary school students in Ondo State.

Recommendations

Based on the findings, the following recommendations are made:

1. Mathematics teachers should deliberately integrate computational-thinking activities into classroom instruction, particularly activities that require students to decompose complex problems, recognise patterns, abstract relevant information, and develop logical solution procedures.

2. Greater emphasis should be placed on algorithmic thinking, given that it made the strongest relative contribution to Mathematics performance. Students should therefore be regularly engaged in tasks requiring them to formulate, sequence, test, and explain mathematical solution procedures.

3. Teacher training programmes should incorporate computational-thinking pedagogy to equip Mathematics teachers with practical strategies for developing these skills alongside conventional mathematical knowledge.

4. Curriculum planners and educational authorities should strengthen the integration of computational thinking into secondary-school Mathematics curricula, rather than treating it as a skill restricted to computer science.

5. Schools should provide students with regular opportunities to solve complex and authentic mathematical problems that require the coordinated use of decomposition, pattern recognition, abstraction, and algorithmic thinking.

Further studies should examine other factors that account for Mathematics performance, since the four computational-thinking components explained 46.0% of the variance, leaving 54.0% associated with other factors not included in the present model.

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