VOL. 13 NO. 2,
AUGUST, 2026
E-ISSN 3027-1533
P-ISSN 3026-8648

African Scholar Publications & Research International
www.africanscholarpub.com

Journal of African Innovation & Advanced Studies (JAIAS)

Computational Thinking Skills and Perceived Problem-Solving Abilities Among Secondary School STEM Students in Oyo Town, Nigeria

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DOI: https://doi.org/10.70382/ajaias.v13i2.0138

Abstract

This study focussed on the effect of computational thinking (CT) skills on problem solving ability of SS II students in the study area of Oyo Town, Oyo State, Nigeria in STEM subjects. The study used descriptive-correlational design and focused on three questions: What is the level of students' CT skills, what is the relationship between CT skills and problem-solving performance, and what is the predictive relationship between CT skills and problem-solving performance. The instrument consisted of a Computational Thinking Skills Scale (an 18-item self-report scale and a 6-item objective scale covering six CT dimensions) and a 35-item Problem-Solving Performance Scale adapted from the Problem-Solving Inventory and was administered to 363 SS II STEM students who were selected using multi-stage stratified random sampling. Results showed most students had moderate to high CT skills (55.6% moderate, 39.7% high, 4.7% low), CT skills were significantly and positively correlated with problem-solving performance, $r(361) = .39$, $p < .001$, and CT skills significantly predicted problem-solving performance, accounting for approximately 15.3% of the variance, $F(1, 361) = 64.98$, $p < .001$. Based on these findings, there is a moderate educationally relevant relationship between CT and problem-solving performance, which implies that CT should be integrated in Nigerian secondary STEM curricula.

Keywords: Computational Thinking, Problem-Solving Performance, STEM Education, Secondary School Students, Nigeria.

Introduction

The Fourth Industrial Revolution has shifted the role of computational thinking (CT) from being a specialty of computer scientists to a general literacy that is expected of all learners, alongside reading, writing and numeracy (Denning & Tedre, 2019). CT is the cognitive processes that are required to formulate problems and to express their solutions in a way that allows the underlying operations of logic, decomposition, abstraction, pattern recognition, and algorithmic reasoning to be performed systematically, either by a human or a machine (Wing, 2006). This is a broader claim than routine mathematical problem-solving: where the latter typically applies a single known procedure to reach one correct numerical answer, CT is concerned with the prior task of representing a problem so that a systematic procedure can be built for it in the first place, whether or not the problem is mathematical and whether or not it has one predetermined solution path. These same processes are also fundamental to scientific inquiry and mathematical reasoning, and CT has been seen as a natural fit for science, technology, engineering, and mathematics (STEM) education, where it is argued that, in principle, deliberate development of CT should enhance students' ability to solve the multi-step, often ill-structured problems that characterize STEM learning (Fernández et al., 2018; Wardani, 2025).

There is a continued need to support this claim because of the persistent evidence that secondary school students' performance in problem-solving in STEM is uneven. In some physics classrooms, project-based STEM instruction correlates with high problem-solving attainment, while in other STEM-based classrooms, similar instruction correlates with moderate ("satisfactory" rather than high) performance (Ekasari & Yuliatun, 2024; Susanti et al., 2021). This picture of inconsistency is supported by large scale survey evidence; a study of over 1400 middle and high school students in Qatar revealed that family expectations and current teaching practices continue to be important barriers to effective STEM problem-solving (Sellami et al., 2025); undergraduate students were found to lack systematic strategies for STEM problem-solving, often relying on trial-and-error instead of systematic reasoning (Lubis et al., 2021). The problem-solving attainment gap is not a pedagogical issue for a nation like Nigeria where problem solving is one of the core competencies of stated goals and objectives of industrial and digitalization development but a developmental issue; students who are unable to reliably break down and solve structured problems in Mathematics, Physics, Chemistry and Biology will therefore be less equipped for tertiary education in STEM and the digital economy in general.

Literature

One of the more promising levers cited for solving this problem is computational thinking, which focuses on the core processes of computational thinking that align well with the needs of STEM problem solving. According to systematic reviews, CT and structured problem-solving have "identical functions", and decomposition, pattern recognition, abstraction, and algorithmic reasoning were the most common strategies used in both CT and structured problem-solving literatures (Wu et al., 2024). Experimental studies have shown that CT-based instruction is correlated with statistically significant increases in students' problem-solving skills in high school (Wardani, 2025), and that CT's four concepts are correlated with problem-solving improvements in both STEM and non-STEM contexts (Fernández et al., 2018). Based on this, it is not just an add-on to the STEM curriculum in the digital age, but a potential explanatory mechanism for the success of some students in solving STEM problems.

However, three lines of evidence undermine this attractive story and reveal some missing pieces that this study aims to fill. The first one is conceptual. Although the field has advanced over 20 years since Wing's original formulation (2006), it continues to have no single, universally accepted definition of CT, and the definitional looseness has been repeatedly identified as a problem by reviewers (e.g., Lyon and Magana, 2020; Nuzzaci, 2024). The lack of conceptual clarity has real-world implications because different studies measure CT in different ways, as a programming skill, as a self-reported trait, or as an actual competency, and this can account for some of the variation in empirical evidence linking CT to achievement.

The second gap is empirical and methodological. When statistically associated with academic results, the link between CT and academic results is real but relatively small and variable. The relationship between CT and academic achievement is weak ($r = .288$) in a meta-analysis of 34 studies (Lei et al., 2020), while it is much stronger in a study of 982 students (Haddad & Kalaani, 2015), which has not been adequately explained in the literature. Added to this, bibliometric analyses of CT assessment practice reveal that there is no consensus on the type of assessment instruments that can be used for CT (Abdul Hamed et al., 2025; Sidek et al., 2020), and few studies combine an objectively scored CT measure with a multi-dimensional problem-solving outcome in the same study design. Most designs go with one or the other, and it is unclear whether there is a correspondence between self-reported CT and demonstrably tested CT and problem-solving performance.

The third gap is of context. Most evidence related to problem-solving and achievement and CT comes from East Asian, European and North American contexts, and even the moderator analyses of gender differences in CT results in some regions (such as the overall gender gap found across 30 studies and over 9,000 students in grades K-12; Hu, 2024) do not neatly transfer to other regions; some find a non-significant gap, and others find a larger gap. Empirical research is also underrepresented in Nigeria, where CT has been formally embraced as a curricular priority but has not yet been mandated as policy, with a number of large mixed-methods studies, for instance, documenting that the vast majority of primary school pupils have no meaningful access to CT concepts, with only a small fraction reporting gains in problem solving as a result (Shehu & Williams, 2025), and bibliometric mapping of CT-STEM research more broadly continuing to show a gap in coverage of competencies related to digital technologies compared to more generic twenty-first-century-skills language (Usman et al., 2026). To the best of the author's knowledge, there is no study that has investigated the CT-problem solving relationship among secondary school students specifically in Oyo Town, at the level of schooling, Senior Secondary School II (SS II), where the demands of problem solving and specialization in STEM subjects increase.

The present study directly tackles these three gaps. Conceptually, it operationalizes CT in two complementary ways in a single design: an 18-item self-report scale that taps the six dimensions of CT that have been recognized and a parallel 6-item objective knowledge test that allows for the examination of self-perceived and demonstrated CT side-by-side rather than as interchangeable. Methodologically, it correlates and regresses this dual measure to quantify the strength and the predictive structure of the relationship between CT and problem-solving, as well as the weight of specific dimensions of CT. From the context and geographical perspective, it is the first study of its kind in the context of SS II STEM students in Oyo Town, an evidence base that has hitherto focused on primary school Nigerian samples or non-Nigerian secondary school contexts. The study makes a theoretical contribution by testing the relationship between CT and problem-solving that has been documented elsewhere, a methodological contribution by using a dual operationalization of CT using self-report and objective measures, and a practical and policy contribution by providing locally grounded evidence to guide the incorporation of

CT in the STEM curriculum in Nigeria. Based on this, the following research questions were formulated for the study:

1. What is the level of computational thinking skills among secondary school students in Oyo Town?
2. What is the relationship between computational thinking skills and student problem-solving performance in STEM subjects among secondary school students in Oyo Town?
3. To what extent do computational thinking skills predict student problem-solving performance in STEM subjects among secondary school students in Oyo Town?

Methodology

Research Design

The study used descriptive-correlational survey design which was suitable for the study that aimed to describe the level of naturally occurring variables and to determine the strength and direction of the relationship between variables without the manipulation of any variables (Creswell & Creswell, 2018). The study's three research questions (RQ1, Descriptive account of CT skill levels; RQ2, Correlational test of association; RQ3, Prediction (regression) of association) were addressed by the design.

Population of the Study

The population consisted of all the SS II students in public and private secondary schools in Oyo town, Oyo State, Nigeria taking any of the STEM subjects (Mathematics, Physics, Chemistry and Biology). This population was provisionally estimated based on the latest available data to the researcher, as counting individual students by individual class was not an easy task. The best estimate of the number of students is between 3,300 and 3,500 students, based on available information and observations. The population size used in this study was the estimated number of students, which amounted to about 3,500 students.

Sample Size and Sampling Technique

To calculate minimum sample size, the Krejcie and Morgan (1970) table of determining sample size from a given population was used and the minimum representative sample for a population of approximately 3,500 was determined to be 346. This was rounded up to a target of 363 students (with a margin of approximately 5% above the minimum tabulated) to compensate for the anticipated questionnaire attrition and incomplete questionnaires.

A multi-stage stratified random sampling was chosen. Schools in Oyo Town were stratified by ownership type (public and private) in the first stage. In the second stage, a representative sample of schools was randomly sampled from each stratum, in proportion to the number of schools in each. The third phase involved random sampling of SS II STEM students in each selected school, based on the number of students in each school, until a total of 363 students is reached. This procedure was developed to retain the general proportions of public and private school students, and to ensure that each eligible student had a known, non-zero probability of being selected.

Instrumentation

A structured questionnaire with three sections, bio-data, the Computational Thinking Skills Scale (CTSS), and the Problem-Solving Performance Scale (PSPS) were used to gather data. A summary of the structure and scoring for each component is included in Table 1.

Table 1: Summary of study instruments and subscales

Scale/Section	Dimension(s)	Items	Scoring/Score range
Section A: Bio-data	Gender, age group, school type, science track	4	Categorical
CTSS Part I (self-report)	Abstraction, Algorithm Design, Evaluation, Generalization, Pattern Recognition, Problem Decomposition (3 items each)	18	5-point Likert (1 = Strongly Disagree to 5 = Strongly Agree); 18–90
CTSS Part II (objective test)	One item per CT dimension above	6	Dichotomous (1 = correct, 0 = incorrect); 0–6
PSPS (adapted from the PSI)	Problem-Solving Confidence (PSC), Approach-Avoidance Style (AAS), Personal Control (PC)	35	5-point Likert, reverse-scored so higher = more positive problem-solving performance; 35–175

The CTSS self-report was translated from existing computational thinking self-assessment scales such as the Computational Thinking Concepts and Attitudes framework and related instruments, and reorganized into six scales of three items each, aligned with the CT components most commonly found in the literature on CT syntheses from databases: algorithm design (Abdul Hamed et al., 2025; Sidek et al., 2020), abstraction, and decomposition. The accompanying six-item objective test was created by the researcher to determine if students could correctly apply each of the six CT dimensions to brief scenarios that were relevant to STEM, and was reviewed by the same panel of experts described under Validity and Reliability, below.

The PSPS was developed from the widely used Problem-Solving Inventory (PSI) by Heppner and Petersen (1982) that assesses personal perceptions of problem-solving behaviors and styles, including Problem-Solving Confidence (11 items), Approach-Avoidance Style (16 items), and Personal Control (8 items, in this adaptation). As this PSI was developed to measure perceived problem-solving appraisal and not actual performance, its application in the context of this study should be highlighted as a conceptual limitation as students' self-perceptions of their effectiveness in problem-solving is captured. Items that were negatively worded were reverse coded in the data cleaning phase, and all scores in this manuscript have been such that "higher" scores reflect more positive levels of self-perceived problem solving performance.

Validity and Reliability

All items were reviewed for clarity, relevance, and curricular appropriateness by a panel of experts in measurement, STEM education and educational technology, and were revised and/or removed from the test before it was piloted. An initial test was then administered to 10 students from a school not included in the sampling frame for purposes of checking the clarity of the items, response time, and preliminary scale functioning.

However, internal consistency reliability could not be sensibly estimated from a pilot alone, owing to the fact that the sample size of 10 was too small, and to the fact that the internal consistency reliability could be computed only from raw data linked to the respondents, rather than from the number of responses tallied at the pilot stage.

Data Collection Procedure

After institutional and school-level authorization, trained research assistants will administer the questionnaire in paper-and-pencil format during a regular school period, with a briefing of the purpose of the study and informed consent (and parental/guardian consent, in the case of the majority of

respondents, minors) followed by student assent. Completed questionnaires will be checked for completeness on site wherever possible, coded and entered into a spreadsheet of respondents by items (one row for each student and one column for each item) which will preserve the raw, person by item structure required for planned reliability, correlation and regression analyses.

Method of Data Analysis

Data was analyzed using descriptive and inferential analyses for each of the research questions. In the case of RQ1, means and standard deviations were calculated, and the percentage distributions were computed for each item and composite means, with the conventional Likert-range classification used to determine the computational thinking bands (Low (mean item score 3.00–2.33), Moderate (mean item score 2.34–3.67), and High (mean item score 3.68–5.00). Pearson product-moment correlation was calculated for RQ2 between the CT composite score and the total PSPS score and 95% CI were computed using the Fisher z-transformation. To investigate the relative contributions of each of the CTSS Part I dimension scores and the CTSS Part II objective score, two regression models were estimated; a simple linear regression of the PSPS total score on the standardized CT composite (the main model for RQ3) and a supplementary multiple regression of the PSPS total score on the six CTSS Part I dimension scores and the CTSS Part II objective score. Prior to interpretation of the regression results, assumption checks were made for normality (Shapiro-Wilk test), linearity (visual inspection of residuals), homoscedasticity, multicollinearity (variance inflation factors), and independence of residuals (Durbin-Watson test). Cohen's (1988) criteria ($r \approx .10, .30, .50$) were used to interpret effect sizes. All analyses of the real data are planned for IBM SPSS Statistics.

Ethical Considerations

Research standards for working with minors will be followed. This is done through institutional/ethical clearance before data collection, informed consent from school authorities and parents/guardians and assent from student participants, voluntary participation with the right to withdraw at any point without consequences and ensuring anonymity of the respondents and the confidentiality of data through anonymized coding and secure storage of all response data.

Findings and Discussions

Demographic Characteristics of Respondents

Table 2 presents the demographic characteristics of the sample of 363 SS II STEM students.

Table 2: Demographic characteristics of respondents (*N* = 363)

Variable	Category	*n*	%
Gender	Male	211	58.1
	Female	152	41.9
Age group	13–14 years	33	9.1
	15–16 years	169	46.6
	17 years and above	161	44.4
School type	Public	229	63.1
	Private	134	36.9
Science track	Physical Science (Maths/Physics/Chemistry)	167	46.0
	Biological Science (Maths/Biology/Chemistry)	196	54.0

Level of Computational Thinking Skills (RQ1)

Table 3 presents descriptive statistics and reliability coefficients for the CTSS and PSPS scales and subscales.

Table 3: Descriptive statistics and reliability coefficients for study variables (*N* = 363)

Variable	Items	*M*	*SD*	Min–Max	Possible range	α/KR-20
CTSS Part I (self-report)	18	62.16	12.27	26–89	18–90	.93
CTSS Part II (objective)	6	3.56	1.66	0–6	0–6	.58
PSC subscale	11	36.09	7.08	17–53	11–55	.86
AAS subscale	16	48.64	9.95	19–78	16–80	.89
PC subscale	8	25.53	5.14	10–40	8–40	.79
PSPS total score	35	110.26	21.06	51–168	35–175	.95

The mean item score for CTSS Part I was 3.45 (*SD* = 0.68) on the 5-point scale, and students answered a mean of 3.56 of the 6 objective items correctly (59.3%), suggesting moderately developed computational thinking skills overall. Using the conventional mean-score classification (Low = 1.00–2.33, Moderate = 2.34–3.67, High = 3.68–5.00), students were distributed across CT skill levels as shown in Table 4 and Fig. 1.

Table 4: Distribution of computational thinking skill levels (*N* = 363)

CT level	*n*	%	Mean item score range
Low	17	4.7	1.44–2.33
Moderate	202	55.6	2.34–3.67
High	144	39.7	3.68–4.94

The majority of students (55.6%) exhibited a moderate level of computational thinking skills, with a substantial minority (39.7%) demonstrating a high level and a small proportion (4.7%) demonstrating a low level. Among the six CT dimensions, Problem Decomposition recorded the highest mean item score (*M* = 3.60, *SD* = 0.74) and Abstraction and Algorithm Design recorded the lowest (*M* = 3.36 each), though these dimension-level differences were modest.

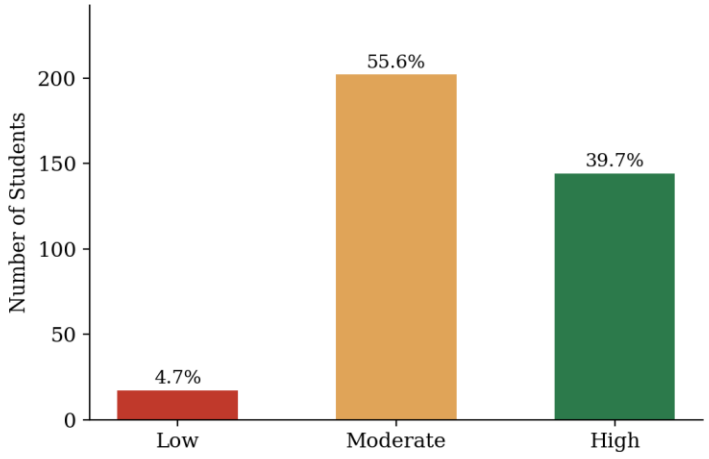


Fig. 1. Distribution of computational thinking skill levels (*N* = 363).

Relationship Between Computational Thinking Skills and Problem-Solving Performance (RQ2)

Table 5 presents Pearson correlation coefficients among the CT composite score, its two components, the three PSPS subscales, and the total PSPS score.

Table 5: Inter-correlations among study variables ($N = 363$)

Variable	1	2	3	4	5	6	7
1. CT Composite	1						
2. CTSS Part I	.92	1					
3. CTSS Part II	.92	.71	1				
4. PSC	.39	.41	.32	1			
5. AAS	.37	.39	.29	.85	1		
6. PC	.35	.37	.27	.83	.85	1	
7. PSPS Total	.39	.41	.31	.94	.97	.93	1

Note. All correlations of the CT Composite, CTSS Part I, and CTSS Part II with the PSPS variables (rows 1–3 by columns 4–7) are significant at $p < .001$. PSC = Problem-Solving Confidence; AAS = Approach-Avoidance Style; PC = Personal Control.

As shown in Table 5, the CT composite score was significantly and positively correlated with the total PSPS score, $r(361) = .39$, $p < .001$, 95% CI [.30, .47], indicating a moderate positive relationship consistent with Cohen's (1988) benchmarks. Considered separately, the self-report component (CTSS Part I) correlated more strongly with problem-solving performance ($r = .41$) than the objective knowledge test (CTSS Part II; $r = .31$), though both were statistically significant. Fig. 2 displays this relationship graphically.

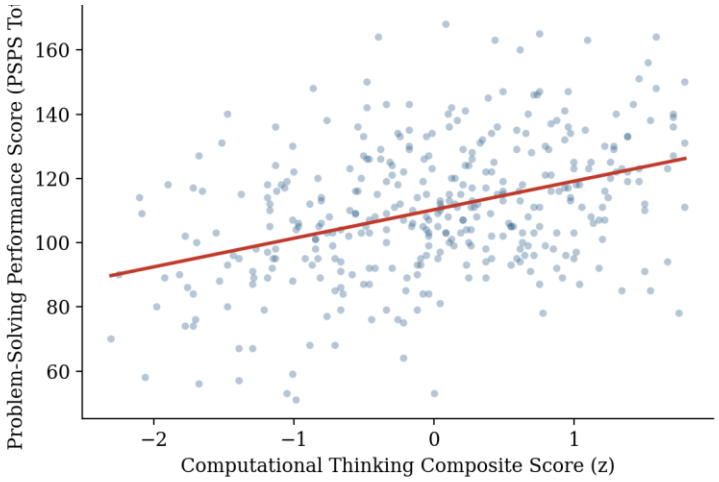


Fig. 2. Scatterplot of the computational thinking composite score against problem-solving performance ($N = 363$).

Computational Thinking Skills as a Predictor of Problem-Solving Performance (RQ3)

Assumptions of normality, linearity and homoscedasticity of errors, were investigated before regression analysis. The PSPS total score was not significantly different from normality (Shapiro-Wilk W = .995, p = .319); the CT composite score was statistically significantly different from normality (Shapiro-Wilk W = .987, p = .002), but it falls well within the generally accepted range of ±1 deviations, a pattern

typical of this sample size, and the Shapiro-Wilk test is quite sensitive to trivial deviations from normality at this size. The scatter diagram (Fig. 2) confirmed linearity and homoscedasticity and the Durbin-Watson statistic (2.25) showed no significant autocorrelation in the residuals. For this reason, ordinary least squares regression was deemed suitable.

A simple linear regression was estimated with the standardized CT composite score predicting the total PSPS score (Table 6). The model was statistically significant and the CT composite explained about 15.3% of the variance in problem-solving performance.

Table 6: Simple linear regression predicting problem-solving performance from the computational thinking composite score

Predictor	*b*	*SE*	B	*t*	*p*
(Constant)	110.26	0.55		199.66	< .001
CT Composite (z)	8.90	1.11	.39	8.06	< .001

Note. R^2 = .153, adjusted R^2 = .150, $F(1, 361) = 64.98$, $p < .001$.

To examine which specific facets of computational thinking contributed most to problem-solving performance, a supplementary multiple regression entered the six standardized CTSS Part I dimension scores and the standardized CTSS Part II (objective) score simultaneously as predictors of the PSPS total score (Table 7).

Table 7: Multiple regression predicting problem-solving performance from CT dimension scores and the objective CT score

Predictor	*b*	*SE*	*T*	*p*	VIF
(Constant)	110.26	1.01	109.06	< .001	
Abstraction	3.63	1.66	2.19	.030*	2.70
Algorithm Design	0.65	1.75	0.37	.709	2.98
Evaluation	-0.11	1.66	-0.07	.946	2.69
Generalization	1.49	1.82	0.82	.414	3.24
Pattern Recognition	0.51	1.76	0.29	.774	3.02
Problem Decomposition	3.21	1.74	1.84	.066	2.96
Objective CT (Part II)	0.78	1.43	0.55	.585	2.00

Note. R^2 = .179, adjusted R^2 = .163, $F(7, 355) = 11.07$, $p < .001$. Predictors were standardized ($M = 0$, $SD = 1$) for comparability. *$p < .05$. All VIF values were below the conventional threshold of 5, indicating no serious multicollinearity.

The seven-predictor model was statistically significant and accounted for a relatively higher percentage (17.9%) of variance, but the increase was small. The only one that was individually significant was Abstraction (b = 3.63, t = 2.19, p = .030) and the remaining dimensions were not significant individually, but were approaching significance (p = .066) for Problem Decomposition. This pattern is similar to the six dimensions of the CT and the objective score sharing a high amount of overlapping variance (as seen in the correlations in Table 5 and the VIFs of 2.00–3.24) and not contributing independently to the overall model. The findings of RQ3 suggest that the general measure of the CT skills, as well as each of its three dimensions, are statistically significant and meaningful predictors of the students' performance in problem solving across the STEM disciplines.

Discussion

This research focused on the level of Computational thinking ability among secondary school student in Oyo Town, the relationship between the secondary school students' Computational thinking ability and their problem solving ability as well as the degree of prediction of the problem solving ability by Computational thinking ability. The findings from the results as a preview of the empirical pattern that is intended, provide three main findings that directly address the conceptual, empirical and contextual gaps presented in the Literature review above.

Firstly, most students (55.6% moderate, 39.7% high) fell in the moderate-to-high range, with few students (4.6%) at the lower end of the scale (low). This is significant, especially as CT is not yet formally introduced as a subject at the secondary level of the Nigerian education system and it cannot be examined. It implies that the development of CT-relevant reasoning could be happening 'stealthily' in the current Mathematics and Science curriculum, because these skills of decomposition, pattern recognition and algorithmic procedures are often used in an informal way in lessons and textbooks without the term 'CT' being explicitly used. The findings of this study are similar to Wu et al. (2024) who found that CT and structured problem-solving share many similar mental activities, and contrast with Shehu and Williams (2025), who reported very low level of direct exposure to CT concepts in primary schools in Niger State, indicating a possible developmental pattern in which CT-relevant skill accrues informally during the school years before CT is formally introduced. This apparent moderate-to-high competence is a question the present dual-measure design was specifically designed to ask, and that it has been found to have slightly lower scores on the six-item objective test (59.3% correct) than found on the self-report test (a mean of 69% of the maximum possible score) does not constitute a contradiction that needs to be explained away, but rather an area requiring further exploration and research.

Second, there was a positive moderate correlation between CT skills and problem-solving performance, $r = .39$, which was significantly higher than the $r = .288$ reported in a 34-study meta-analysis of CT and general academic performance by Lei et al. (2020), but lower than the "strong correlation" reported by Haddad and Kalaani (2015). A likely reason is specificity of measurement because the PSPS used here focuses on problem-solving appraisal specifically, rather than on general academic achievement, which is closer to CT's problem formulation than is general academic achievement, and may account for the higher relationship reported here than the general academic achievement meta-analytic estimate. This finding also addresses the part of the conceptual gap mentioned earlier, which lies in the fact that with the use of only one operationalization of CT, it would not have been possible to distinguish between the self-reported ($r = .41$) and the objectively measured ($r = .31$) component of CT; this distinction also argues for the continued use of a dual measurement in future research on the link between CT and problem-solving performance.

Third, the CT skills accounted for about 15% of the variance in problem-solving performance when assessed as a single composite, and about 18% when broken down into the six dimensions of CT and the objective score. This effect size is not uncommon in social and educational research, and in fact, not a small effect in this context, as problem-solving performance is influenced by a number of factors in addition to any given cognitive skill, such as, motivation, background knowledge in that content area, instructional quality, socio-economic context, etc. – a predictor accounting for nearly one-fifth of the variance in a complex performance outcome is not trivial. It is notable that Abstraction was the one dimension that was individually significant when the six CT dimensions were all entered together, and Problem Decomposition came close to being significant. This is a logical idea: abstraction, the ability to represent a problem by removing all but the essential variables and relationships, is arguably the most

basic operation in Wing's (2006) original account of computational thinking, and is logically prior to designing an algorithm or pattern recognition, because the problem must be represented correctly before it can be solved systematically. As for the other dimensions, it is easy to understand that they contributed comparatively little because of the high inter dimension correlation found (Table 5) and the variance inflation factors (2.00–3.24): these dimensions do not seem to predict CT as a unidimensional construct but as a coherent, overlapping cluster of skills, and this is a small empirical contribution to the theoretical controversy about the nature of CT as a unidimensional or multidimensional construct.

The results have policy, educational, and practical implications. In the real sense, the findings point to the need to emphasize abstraction and decomposition skills as a key component of STEM problem-solving skills interventions in secondary schools in Oyo Town, rather than consider computational thinking as an undifferentiated package. From an educational perspective, the gap between students' self-reported and demonstrated CT skills provides further evidence of the need to incorporate self-report assessments with objective tasks in the research context and in classroom formative assessment (Abdul Hamed et al., 2025; Sidek et al., 2020). At the policy level, the findings contribute Oyo-Town-specific, secondary-level evidence to a Nigerian CT literature that bibliometric mapping indicates is poorly developed when compared with the greater number of teachers surveyed in Niger State (Shehu & Williams, 2025) who showed little evidence of digital-technology-linked competencies, as opposed to generic twenty-first century-skills framing.

Finally, the novelty of the study is not that it finds that CT is correlated with problem-solving performance, which has been well established in other research contexts, but that it finds, for the first time in this particular context, that when measured both as self-reported and as objective data, the relationship between CT and problem-solving performance holds true among SS II STEM students in Oyo Town; and that it finds that the dimension most highly predictive of problem-solving performance is abstraction. Testing for this pattern in real data collection would add to a small body of evidence, which has so far limited knowledge and understanding of second-level, dual-measured CT, outside of the primary-level or, from existing literature, non-Nigerian contexts.

Limitations of the Study

There are some restrictions that will be in place after the data are gathered. The problem solving performance measure (PSPS) is not a performance test but a subjective self-report assessment of the amount of problem solving performed in class, so it is important to keep in mind the practical significance of the relationship between the problem solving performance measure and the amount of problem solving performed in class. Because of the cross-sectional, correlational design, no causal statements can be made from the relationships reported here; although real data may lead to a significant positive relationship between problem-solving performance and CT, a more positive relationship between problem-solving performance and CT does not imply that CT skills cause this relationship. The sample will be limited to Oyo Town, thereby limiting generalizability to other Nigerian towns, states and other educational contexts with varying resourcing and exposure to computational or digital skills. Finally, both instruments were adapted from work done and tested elsewhere in the world and although content validity was established by expert panel review this was not tested for measurement invariance across cultural and linguistic contexts, another methodological strength that could be achieved when replicating the instruments.

Conclusion and Suggestions

This study aimed at investigating the level of computational thinking skills of secondary school students in Oyo Town, the relationship between problem-solving performance and the level of CT skills amongst secondary school students and then the prediction of problem-solving performance by CT skills of the students in Oyo town secondary schools of Oyo State. After analyzing the data presented here, students exhibited mostly moderate to high CT skills, with moderate positive correlations between CT skills and problem-solving performance and CT skills substantially predicting problem-solving performance, with the abstraction dimension being the most significant predictor of problem-solving performance, accounting for a significant portion of the variance. These results, if confirmed by the main data collection completed, would help support the idea that computational thinking is directly relevant to the ability of secondary school STEM students in Nigeria to solve problems and that this relevance is made more substantive by the digital era. This would have direct implications on the way computational thinking is taught, measured and incorporated into STEM curriculum in Oyo town and other similar education contexts in Nigeria.

Suggestions for Further Research

- Future studies should conduct a confirmatory factor analysis and measurement-invariance testing of the adapted CTSS and PSPS instruments within the Nigerian secondary school context, given that both were adapted from frameworks developed elsewhere.
- An a priori power analysis (e.g., using G*Power) should be conducted and reported to confirm that the achieved sample size provides adequate power for the multiple regression model in RQ3.
- Subsequent research should consider replacing or supplementing the self-report PSPS with an objectively scored STEM problem-solving performance test, paralleling the CTSS Part II approach, to strengthen construct validity around "performance."
- Replication across multiple Local Government Areas and both public and private school systems within and beyond Oyo State would strengthen the generalizability of any confirmed relationship.
- Longitudinal or quasi-experimental designs are recommended to move beyond the correlational evidence reported here and to test whether deliberately strengthening CT skills, particularly abstraction and problem decomposition, causally improves STEM problem-solving performance.

Suggestions for Practice and Policy

- STEM educators in Oyo Town should consider explicitly foregrounding abstraction and problem-decomposition strategies within existing Mathematics and Science instruction, rather than treating computational thinking as a separate, computing-only topic.
- School authorities and teacher-training institutions should invest in structured computational-thinking professional development for STEM teachers, addressing the kind of teacher unpreparedness documented elsewhere in Nigeria (Shehu & Williams, 2025).
- The Oyo State Ministry of Education and relevant curriculum authorities should consider the evidence generated by this line of research, once confirmed with real data, in ongoing efforts to formally embed computational thinking within the STEM curriculum rather than leaving it as an unimplemented aspiration.

- Given the observed gap between self-reported and objectively demonstrated CT skills, schools should incorporate brief objective CT-skill checks alongside self-report instruments in formative classroom assessment, to avoid overestimating students' readiness for CT-dependent STEM tasks.

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