

IMPACT OF AI-POWERED SMART SCHOOLS ON COMPUTATIONAL THINKING AND PROBLEM-SOLVING SKILLS AMONG SECONDARY SCHOOL STUDENTS IN ENUGU STATE

Lilian Ezugwu

Department of Computer Science Education, Enugu State College of Education, Technical, Enugu
Corresponding author: Lilian Ezugwu

ABSTRACT

This study investigated the impact of AI-powered smart school environments on the development of computational thinking (CT) and problem-solving skills among secondary school students in Enugu State, Nigeria. Employing a quasi-experimental pretest-posttest design, a total of 100 students drawn from six secondary schools across urban and semi-urban areas of Enugu State participated in a 12-week intervention programme. Participants were exposed to AI-integrated learning platforms, including adaptive tutoring systems, intelligent feedback tools, and algorithmic thinking modules. Standardised instruments, the Computational Thinking Assessment Scale (CTAS) and the Problem-Solving Proficiency Test (PSPT) were used for data collection, and results were analysed using paired-samples t-tests and ANCOVA at a significance level of 0.05. Findings revealed a statistically significant improvement in CT sub-skills decomposition, pattern recognition, abstraction, and algorithm design, as well as overall problem-solving performance ($p < .001$) following the AI-smart school intervention. Private schools showed significantly higher CT gains than public schools, whereas no statistically significant gender-based difference was observed. The study concludes that AI-powered smart school environments meaningfully enhance CT and problem-solving skills in secondary school students and recommends scaled integration of AI tools into the Nigerian secondary school curriculum.

Keywords: AI-powered smart schools; computational thinking; problem-solving skills; secondary education; Enugu State; Nigeria; educational technology

1. Introduction

The rapid proliferation of artificial intelligence (AI) technologies across sectors has generated increasing pressure on educational systems worldwide to prepare learners with competencies relevant to a digital economy. Among these competencies, computational thinking (CT) and problem-solving skills have been identified as foundational capacities that enable individuals to engage meaningfully with technology-driven environments (Wing, 2006; Voogt et al., 2015). Computational thinking, broadly defined as the ability to decompose complex problems, identify patterns, construct abstractions, and design algorithmic solutions, has gained significant traction as a 21st-century skill that transcends computer science and is applicable across diverse disciplines (Brennan & Resnick, 2012; ISTE, 2016).

In Nigeria, despite ambitious national policies such as the National Digital Economy Policy and Strategy (NDEPS 2020-2030) and the Federal Ministry of Education's Strategic Plan for the integration of technology in schools, the practical translation of these frameworks into classroom realities remains uneven. Secondary schools in Enugu State, like many across the South-East geopolitical zone, continue to grapple with inadequate instructional technology infrastructure, outdated pedagogical approaches, and a dearth of qualified teachers capable of delivering technology-integrated lessons (Okonkwo & Eze, 2021; Ugwuanyi et al., 2022). These challenges are compounded by a curriculum that, while having been revised in recent years, still inadequately emphasizes digital literacy and CT at the secondary level.

AI-powered smart schools represent a transformative paradigm in education one that leverages adaptive learning systems, intelligent tutoring platforms, automated feedback mechanisms, and data analytics to personalise instruction and enhance learner engagement (Luckin et al., 2016; Chen et al., 2020). These environments move beyond the static deployment of computers in classrooms, offering instead dynamic, responsive, and student-centred digital ecosystems capable of adjusting content, pacing, and assessment to individual learner needs. Existing research from developed economies and emerging economies alike has highlighted the potential of AI-integrated educational environments to significantly improve students' CT skills, logical reasoning, and problem-solving performance (Su et al., 2020; Sáez-López et al., 2021). However, there remains a conspicuous gap in empirical evidence from sub-Saharan African contexts, particularly Nigeria, where socioeconomic, infrastructural, and cultural factors create a distinctly different educational landscape.

This study was therefore designed to address this gap by empirically investigating the impact of AI-powered smart school interventions on computational thinking and problem-solving skills among secondary school students in Enugu State. In doing so, the study contributes to a growing body of knowledge on educational technology in developing country contexts and offers evidence-based insights to guide policy and practice in Nigerian secondary education.

1.1 Statement of the Problem

Despite the global enthusiasm for AI integration in education, empirical studies examining its effect on CT and problem-solving skills in Nigerian secondary schools remain sparse. Most secondary school students in Enugu State are taught with conventional, lecture-centred methods that do not foster higher-order cognitive skills such as problem decomposition, logical sequencing, and algorithmic reasoning. The absence of AI-enabled learning tools in most public secondary schools perpetuates rote memorisation and passive learning, resulting in graduates who are ill-equipped for the demands of the digital economy. This study seeks to provide empirical evidence on whether AI-powered smart school environments can serve as a viable and effective intervention for developing these critical competencies among secondary school students in Enugu State.

1.2 Objectives of the Study

The specific objectives of this study were to:

Assess the pre-intervention and post-intervention levels of computational thinking skills among secondary school students exposed to AI-powered smart school environments in Enugu State.

Determine whether AI-powered smart school interventions significantly improve students' problem-solving skills.

Examine the influence of gender on CT skill development within AI-enhanced learning environments.

Compare the CT performance gains of students in public and private secondary schools following the intervention.

1.3 Research Questions

The following research questions guided the study:

What are the pre- and post-intervention computational thinking skill levels of secondary school students exposed to AI-powered smart school environments?

Do AI-powered smart school interventions significantly improve problem-solving skills among secondary school students?

Is there a significant difference in CT skill development between male and female students in AI-enabled environments?

Do students in private schools demonstrate significantly greater CT gains than those in public schools following the intervention?

1.4 Hypotheses

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

H01: AI-powered smart school environments have no statistically significant effect on the computational thinking skills of secondary school students in Enugu State.

H02: There is no statistically significant difference in computational thinking gains between male and female secondary school students in AI-powered smart school environments.

H03: There is no statistically significant difference in CT performance gains between students in public and private secondary schools following AI-powered smart school intervention.

H04: AI-powered smart school tools have no statistically significant effect on the problem-solving skills of secondary school students in Enugu State.

2. Literature Review

2.1 Conceptual Framework

The conceptual underpinning of this study draws on three inter-related constructs: AI-powered smart schools, computational thinking, and problem-solving skills. Jeong et al. (2021) defines AI-powered smart schools as digitally enhanced learning environments that integrate AI technologies, including machine learning, natural language processing, adaptive algorithms, and intelligent analytics, to create personalised, data-driven, and interactive educational experiences. Unlike traditional computer-aided instruction, AI-powered smart schools continuously learn from student interactions, making real-time adjustments to content delivery, difficulty level, and formative feedback (Roll & Wylie, 2016).

Computational thinking, as conceptualised by Wing (2006) and later operationalised by Brennan and Resnick (2012), encompasses four core cognitive processes: (1) decomposition, breaking problems into manageable sub-components; (2) pattern recognition, identifying similarities, trends, and regularities across problems; (3) abstraction, filtering essential information from irrelevant details; and (4) algorithmic thinking, designing step-by-step procedures for problem resolution. These sub-skills collectively form the bedrock of logical, structured, and systematic approaches to complex challenges.

Problem-solving, within educational psychology, is understood as the cognitive process by which individuals identify a goal, diagnose obstacles, generate solution pathways, and evaluate outcomes (Jonassen, 1997; Schoenfeld, 2013). It is intimately connected to CT in that effective problem-solving increasingly requires computational approaches, particularly in STEM-related domains. The theoretical framework of this study integrates Vygotsky's Zone of Proximal Development (ZPD) with AI-facilitated scaffolding, positing that AI systems can serve as intelligent interlocutors that dynamically extend student capability beyond their independent competence levels.

2.2 AI-Powered Smart Schools: Global Developments

The global discourse on AI in education has accelerated considerably since the publication of seminal reports by UNESCO (2019), the World Economic Forum (2020), and the OECD (2021), all of which advocate for strategic AI integration in K-12 education. In China, the AI Education project piloted in schools across Shanghai and Hangzhou demonstrated that AI-powered adaptive platforms improved mathematics problem-solving scores by an average of 28% over a semester (Li et al., 2021). Similarly, in the United States, the implementation of Carnegie Learning's MATHia platform across multiple school districts yielded statistically significant improvements in algebraic reasoning, a domain closely associated with CT skills (Ritter et al., 2019).

In sub-Saharan Africa, initiatives such as Kenya's Digital Literacy Programme (DLP), Rwanda's Smart Classroom Project, and South Africa's Siyavula adaptive learning platform have demonstrated contextually sensitive models for AI integration that account for bandwidth limitations, device constraints, and local curriculum requirements (Mureithi & Muthoni, 2020; Siyavula, 2022). These models underscore the importance of designing AI educational tools that are culturally responsive, infrastructure-aware, and pedagogically aligned with national curricula, considerations especially relevant to the Nigerian context.

2.3 Computational Thinking in Secondary Education

The integration of CT into secondary education curricula has garnered considerable scholarly attention over the past decade. Grover and Pea (2013) argue that CT should be treated not as a supplementary digital literacy skill but as a core cognitive competency to be explicitly taught across subject areas. Their review of CT intervention studies found that programming environments, robotics, and problem-based learning tasks were the most effective pedagogical tools for developing CT skills among K-12 learners. More recent meta-analyses by Scherer et al. (2019) and Sun et al. (2021) corroborate these findings, reporting significant positive effect sizes for CT-focused interventions in secondary school settings globally.

In Nigeria, the 2013 and 2023 revisions of the Senior Secondary School Curriculum by the Nigerian Educational Research and Development Council (NERDC) incorporated elements of ICT and computer applications; however, explicit CT frameworks and AI literacy components remain absent from mainstream classroom delivery (Okonkwo & Eze, 2021). Studies by Ugwuanyi et al. (2022) and Mbah and Okafor (2023) highlight persistent teacher capacity deficits, unreliable electricity supply, and inadequate digital infrastructure as the principal barriers to effective CT education in Enugu State secondary schools.

2.4 AI and Problem-Solving Skills

Empirical evidence linking AI-mediated learning environments to improved problem-solving skills is growing. Chen et al. (2020) conducted a systematic review of 43 studies on AI in education and found that AI-powered tutoring systems produced a weighted mean effect size of $d = 0.76$ for problem-solving outcomes, significantly surpassing conventional instructional approaches. Sáez-López et al. (2021) similarly found that students in AI-enriched classrooms in Spain demonstrated superior performance on open-ended problem-solving tasks relative to control groups. These gains were attributed to the personalised feedback loops, immediate error diagnosis, and branched learning pathways inherent in AI systems.

Within the Nigerian educational research landscape, however, the empirical evidence base remains comparatively thin. Eze and Okonkwo (2022) investigated the effect of computer-based instruction on problem-solving performance in secondary school mathematics in Enugu State and found modest but significant improvements. Their study did not, however, examine AI-specific pedagogical features. The present study therefore advances this line of inquiry by specifically targeting AI-powered, adaptive smart school environments as the intervention modality.

3. Methodology

3.1 Research Design

This study adopted a quasi-experimental pretest-posttest non-equivalent control group design. This design was considered appropriate given that intact school classes were used as study groups, and random assignment of individual students to experimental and control conditions was not feasible. The experimental group received the AI-powered smart school intervention over 12 weeks, while the control group continued with conventional classroom instruction. Baseline equivalence between groups was established through pretest score comparisons and verified using independent-samples t-tests prior to the intervention.

3.2 Population and Sample

The target population comprised all junior secondary school (JSS 3) and senior secondary school (SSS 1 and SSS 2) students in Enugu State, totalling approximately 48,600 students across 312 public and private secondary schools (Enugu State Ministry of Education, 2023). A purposive-stratified sampling technique was employed to select six secondary schools three public and three private from Enugu North, Enugu South, and Enugu East Local Government Areas. Within each selected school, intact classes were randomly assigned to either the experimental (AI-smart school) or control (conventional instruction) condition. A total of 100 students (50 experimental, 50 control) constituted the final sample after accounting for attrition.

3.3 Research Instruments

Two standardised instruments were used for data collection:

(i) Computational Thinking Assessment Scale (CTAS): A 40-item instrument adapted from the Computational Thinking Scale (CTS) developed by Korkmaz et al. (2017) and contextualised for the Nigerian secondary curriculum. The CTAS assessed four sub-scales: decomposition (10 items), pattern recognition (10 items), abstraction (10 items), and algorithm design (10 items). Reliability of the CTAS was established through Cronbach's alpha ($\alpha = 0.87$), and content validity was verified by a panel of six CT experts.

(ii) Problem-Solving Proficiency Test (PSPT): A 25-item scenario-based assessment instrument designed to measure students' capacity to identify problem components, generate solution strategies, and evaluate outcomes. The PSPT was scored on a 100-point scale. Cronbach's alpha for the PSPT was 0.83, and face and content validity were confirmed by independent expert reviewers.

3.4 The AI-Powered Smart School Intervention

The intervention was implemented through a combination of three AI platforms deployed across six computer-equipped laboratory sessions per week over 12 weeks. The platforms used were:

Khan Academy Kids and Khanmigo (AI tutoring chatbot): used for personalised mathematics and logic problem scaffolding, adaptive practice, and real-time feedback;

Scratch 3.0 with AI extensions: used for block-based programming activities targeting decomposition, pattern recognition, and algorithm design;

Google's Teachable Machine and AutoML tools: used for introductory machine learning activities that reinforced abstraction and data-driven problem-solving.

Each session was 90 minutes in duration and was facilitated by trained teacher-researchers. The control group received equivalent instructional time but using conventional chalk-and-board teaching and standard textbooks.

3.5 Data Collection and Analysis Procedure

The CTAS and PSPT were administered as pretests one week before the intervention commenced and as posttests within one week of its conclusion. Demographic data were collected via a structured questionnaire. All quantitative data were analysed using IBM SPSS Statistics Version 27. Paired-samples t-tests were used to compare pre- and post-intervention scores within the experimental group. Independent-samples t-tests were employed to examine gender and school-type differences in CT gains. ANCOVA was used to control for pretest differences when comparing group outcomes. Statistical significance was set at $\alpha = 0.05$.

4. Results And Discussion

4.1 Demographic Profile of Participants

Table 1: Demographic Profile of Participants (N = 100)

Variable	Category	Frequency (%)
Gender	Male	52 (52.0%)
	Female	48 (48.0%)
School Type	Public	60 (60.0%)
	Private	40 (40.0%)
Class Level	JSS 3	45 (45.0%)
	SSS 1	30 (30.0%)
Prior AI Exposure	SSS 2	25 (25.0%)
	None	35 (35.0%)
	Moderate	43 (43.0%)
	High	22 (22.0%)

The sample comprised 52 male and 48 female students. Public school students accounted for 60% of the sample, while 40% were from private schools. The majority of participants (45%) were in JSS 3, with 30% in SSS 1 and 25% in SSS 2. Prior exposure to AI-related tools was limited, with 35% reporting no prior exposure, underscoring the novelty of the intervention for a large proportion of participants.

4.2 Pre- and Post-Intervention Computational Thinking and Problem-Solving Scores

Table 2: Pre- and Post-Intervention CT and Problem-Solving Scores (N = 50, Experimental Group)

Skill Domain	Pre-test Mean	Post-test Mean	Mean Gain	Std Dev	p-value
Decomposition	38.4	72.6	+34.2	6.21	<.001
Pattern Recognition	41.2	74.8	+33.6	5.87	<.001
Abstraction	35.9	69.3	+33.4	7.14	<.001
Algorithm Design	32.1	68.7	+36.6	6.93	<.001
Problem-Solving	40.3	76.2	+35.9	5.56	<.001
Overall CT Score	37.6	72.3	+34.7	6.34	<.001

The results in Table 2 reveal substantial and statistically significant gains across all CT sub-skills and overall problem-solving performance following the intervention. The largest improvement was observed in algorithm design (+36.6 points), closely followed by problem-solving (+35.9 points) and decomposition (+34.2 points). All gains were statistically significant at $p < .001$, indicating that the observed improvements are unlikely to be attributable to chance. The consistently high mean gains across all dimensions suggest that AI-powered smart

school environments produced broad-spectrum improvements in CT-related cognitive skills.

4.3 Hypothesis Testing

Table 3: Summary of Hypothesis Testing Results

Hypothesis	t-value	df	p-value	Decision
H01: AI smart schools have no significant effect on CT skills	18.34	99	<.001	Rejected
H02: No significant difference in CT gains by gender	1.27	98	0.207	Retained
H03: No significant difference in CT gains by school type	4.91	98	<.001	Rejected
H04: AI tools have no significant effect on problem-solving	16.82	99	<.001	Rejected

H01 Effect of AI Smart Schools on CT Skills: The paired-samples t-test yielded $t(99) = 18.34$, $p < .001$, leading to the rejection of H01. This confirms that AI-powered smart school environments produced a statistically significant improvement in the computational thinking skills of participants. This finding aligns with those of Chen et al. (2020), Su et al. (2020), and Sáez-López et al. (2021), all of whom documented significant CT improvements in AI-enriched learning environments.

H02 Gender Differences in CT Gains: The independent-samples t-test comparing CT gains between male and female students returned $t(98) = 1.27$, $p = 0.207$, indicating no statistically significant gender-based difference in CT development. H02 was therefore retained. This finding is consistent with Scherer et al.'s (2019) meta-analysis, which reported that well-designed CT interventions tend to be gender-equitable in their outcomes. It suggests that AI-powered platforms may offer a democratising effect on CT learning, transcending gender-related differences in technology confidence often observed in traditional computing education.

H03 School Type Differences in CT Gains: Comparison of CT gains between public and private school students revealed $t(98) = 4.91$, $p < .001$, leading to the rejection of H03. Private school students demonstrated significantly higher CT gains than their public school counterparts. This disparity may be attributable to better baseline IT infrastructure, more reliable internet connectivity, greater device-to-student ratios, and more experienced facilitators in private institutions, factors that amplified the effectiveness of the AI intervention.

H04 Effect of AI Tools on Problem-Solving: The analysis confirmed a significant effect of the AI-powered smart school intervention on problem-solving skills, $t(99) = 16.82$, $p < .001$, resulting in the rejection of H04. Students who underwent the intervention demonstrated substantially improved scores on the PSPT. These findings corroborate the theoretical assertions of Jonassen (1997) regarding the importance of technology-mediated environments for developing higher-order problem-solving cognition.

4.4 Discussion

The aggregate findings of this study provide compelling empirical evidence that AI-powered smart school environments significantly enhance both computational thinking and problem-solving skills among secondary school students in Enugu State. The magnitude of the improvements, with overall CT scores increasing by nearly 35 percentage points on average, surpasses the gains typically reported in studies employing conventional computer-based instruction and is consistent with the elevated effect sizes documented in AI-specific educational technology interventions globally (Chen et al., 2020; Ritter et al., 2019).

The adaptive, personalised, and responsive nature of the AI platforms used in the intervention is posited as the primary mechanism underlying these gains. Unlike static educational software, the AI systems deployed in this study continuously recalibrated task difficulty, offered targeted hints and error diagnostics, and provided individualised learning pathways features consistent with Vygotsky's ZPD framework, wherein learning is most effective when challenges are optimally calibrated to the learner's current ability level. The immediate feedback loops inherent in AI tutoring platforms appear to have been particularly efficacious in developing algorithm design skills, which require iterative testing, debugging, and revision cognitive processes that benefit immensely from rapid, specific feedback (Luckin et al. 2016).

The absence of significant gender-based differences in CT development is an encouraging finding that challenges prevailing assumptions about gender-technology gaps in Nigerian secondary education. It suggests that, when access to AI tools is equalised, as was the case in this intervention, female students are equally capable of attaining high levels of CT proficiency. This finding has important equity implications for the design and implementation of AI-educational interventions and underscores the need to address structural access barriers rather than attribute performance gaps to inherent gender-related cognitive differences.

Conversely, the significantly higher CT gains observed among private school students relative to public school students reflect systemic inequities in educational infrastructure and resource distribution that persist across the Nigerian school system. While AI-powered smart schools hold transformative potential, the realisation of this potential is contingent on foundational digital infrastructure: reliable electricity, stable internet connectivity, adequate computing devices, and trained facilitation staff, which are currently more robustly available in private institutions. This finding calls attention to the urgent need for targeted government investment in public school digital infrastructure as a prerequisite for equitable AI-in-education outcomes.

5. Conclusion And Recommendations

5.1 Conclusion

This study set out to empirically investigate the impact of AI-powered smart school environments on computational thinking and problem-solving skills among secondary school students in Enugu State, Nigeria. The findings provide robust, statistically significant evidence that AI-powered smart school interventions substantially improve CT sub-skills, including decomposition, pattern recognition, abstraction, and algorithm design, as well as overall problem-solving performance. The intervention demonstrated gender equity in its effects, affirming that AI-powered learning environments can bridge rather than widen gender gaps in CT education. However, the significant advantage enjoyed by private school students underlines the systemic infrastructure disparities that mediate the effectiveness of technology-based educational interventions in the Nigerian context.

These findings position AI-powered smart school integration as a high-impact strategy for developing the cognitive competencies necessary for participation in the 21st-century digital economy and contribute a contextually grounded evidence base to the growing global literature on AI in secondary education.

5.2 Recommendations

Based on the findings and conclusions, the following recommendations are made:

The Enugu State Ministry of Education and the Federal Ministry of Education should develop and implement a phased policy framework for the systematic integration of AI-powered educational tools into the secondary school curriculum, with explicit targets for CT and digital literacy outcomes.

Substantial and prioritised investment in digital infrastructure, including reliable power supply via solar alternatives, the provision of computing devices, and broadband internet access, is urgently needed in public secondary schools in Enugu State to ensure equitable access to AI-educational tools.

Pre-service and in-service teacher training programmes at Colleges of Education and universities in Enugu State, including the Enugu State College of Education Technical, should incorporate AI literacy, CT pedagogy, and the facilitation of AI-powered learning environments as core competency areas.

Future longitudinal research should track the sustained effects of AI-smart school interventions on CT and problem-solving skills beyond the immediate post-intervention period, and should examine how gains transfer to standardised academic performance in STEM subjects.

Public-private partnerships should be explored as a mechanism for leveraging the superior infrastructure of private schools to benefit students in adjacent public institutions through shared AI-learning facilities, resource pooling, and collaborative professional development.

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