DIGITAL INFRASTRUCTURE, STUDENT READINESS, AND SCHOOL TYPE AS DETERMINANTS OF AI ADOPTION IN SEMI-URBAN SECONDARY SCHOOLS IN RIVERS STATE, NIGERIA

[1]Ahiamadu Jonathan Okirie & [2]Emmanuel Uwhekadom Ejimaji

Federal College of Education (Technical), Omoku, PMB 11, Rivers State, Nigeria

[1]okirie575@gmail.com
[2]eejimaji@gmail.com

Abstract

This study examined the influence of digital infrastructure, student readiness, and school type on the adoption of Artificial Intelligence technologies among Senior Secondary Three (SS3) students in Omoku, Rivers State. Utilizing the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) frameworks, a descriptive survey research design was employed to investigate the extent to which these factors shape students' ability to integrate AI into their learning activities. The population comprised 1,013 SS3 students from twenty secondary schools in Omoku. Using Taro Yamane's sampling formula at a 95% confidence level and 5% margin of error, a sample size of 287 students was obtained through stratified proportional sampling. Data were collected using a structured questionnaire. The instrument was subjected to face and content validity, and its reliability was confirmed through Cronbach's Alpha, which yielded a coefficient of 0.837. The data were analyzed using SPSS, employing one-sample and independent-sample t-tests); and inferential statistics conducted at the 0.05 level of significance. Findings revealed that digital infrastructure for AI-based learning is moderately available overall (mean = 3.30), though a considerable disparity exists between private schools (mean = 3.76) and public schools (mean = 2.34). Students demonstrated moderate readiness to adopt AI technologies (mean = 3.39), indicating generally positive attitudes toward AI-assisted learning. However, AI adoption levels were notably higher in private schools (mean = 3.53) than in public schools (mean = 3.09). The study concludes that while students show willingness to adopt AI, infrastructural disparities and school type remarkably influence the extent of adoption. These insights contribute to educational planning, teacher training, and Nigeria's broader digital transformation agenda.

KEYWORDS: AI adoption, digital infrastructure, school type, secondary education, semi–urban Nigeria, student readiness, UTAUT

Introduction

Artificial Intelligence, defined as computer-based systems capable of perfo3rming tasks that require human intelligence such as learning, problem-solving, and decision-3making, has rapidly advanced and reshaped educational systems worldwide (Zhang et al., 2025). In this study, AI is applied to support educational activities, offering opportunities for personalized learning, administrative efficiency, and improved student outcomes (Hwang & Tu, 2024). AI-based learning refers to instructional strategies that employ AI technologies to enhance outcomes through personalized guidance, intelligent feedback, and adaptive systems. Tools such as tutoring applications, adaptive platforms, and automated assessments are increasingly integrated into classrooms to improve teaching practices and student experiences. While these innovations are transforming secondary education in developed countries, several developing nations, including Nigeria, remain in the early stages of adoption due to infrastructural, socio-economic, and institutional challenges (Rana et al., 2024; Mienye et al., 2024).

Education in Nigeria is widely recognized as a pathway for national development and individual empowerment (Obed-Chukwuka, 2025; Anorue et al., 2024). Senior Secondary Three (SS3) students occupy a critical position as they prepare for external examinations and transition into higher education or vocational careers. Integrating AI into their learning could provide tailored support, improve exam preparation efficiency, and foster digital competencies essential for the 21st century. However, studies highlight that adoption in Nigerian secondary schools depends on contextual factors such as digital infrastructure, student readiness, and school type (Abodunrin et al., 2025).

Digital infrastructure, comprising internet connectivity, computers, electricity, and ICT facilities, plays a foundational role in enabling AI-based learning. Reliable internet, functional devices, and stable electricity are prerequisites for deploying AI technologies (Mutiso, 2024). Yet, many Nigerian schools, especially in semi-urban and rural areas, face infrastructural deficits that hinder effective use of digital tools (John & Aliyu, 2024). In Omoku, a semi-urban community in Rivers State, these challenges are particularly evident, raising concerns about equitable access to AI-driven education.

Student readiness is another determinant of adoption, encompassing digital literacy, motivation, and openness to new learning methods. Research shows that Nigerian students often lack adequate exposure to emerging technologies, limiting their ability to fully engage with AI tools (Umennuihe et al., 2023; Onuyi, 2024). Without sufficient training and awareness, even well-equipped schools may struggle to achieve meaningful integration.

School type further shapes adoption. Private schools, generally better resourced, provide greater access to ICT facilities and innovative teaching practices compared to public schools (Odeajo & Odefadehan, 2025). This disparity raises equity concerns, as private school students in Omoku are more likely to benefit from AI technologies, potentially widening the digital divide.

Despite growing discourse on AI in education, empirical research on secondary school students in smaller Nigerian communities like Omoku remains limited. Most studies emphasize national or urban contexts, leaving a gap in understanding local conditions. This gap extends not only to geographical representation but also to unanswered conceptual and empirical questions, such as how specific variables interact or whether constructs from models like

TAM/UTAUT operate differently in semi-urban Nigerian contexts. Addressing this deficiency is crucial, as localized evidence can inform policies tailored to the unique needs of semi-urban schools.

This study therefore examines the influence of digital infrastructure, student readiness, and school type on AI adoption among SS3 students in Omoku. By investigating these factors, it aims to provide insights into the conditions necessary for equitable and effective integration of AI technologies in Nigerian secondary education.

Statement of the problem

Artificial Intelligence is increasingly integrated into education worldwide, yet empirical evidence shows uneven implementation in Nigeria, particularly at the secondary school level. In Omoku, Rivers State, SS3 students preparing for national examinations face measurable barriers to AI adoption. Infrastructural deficits are evident: unreliable internet, unstable electricity, and limited ICT facilities continue to constrain access to digital learning tools (Orji & Ukeh, 2022). Student readiness is also empirically limited, with documented gaps in digital literacy, motivation, and exposure that reduce effective engagement with AI technologies (Nwuke & Yellowe, 2025). These challenges are compounded by institutional disparities. Public schools consistently report weaker infrastructural support compared to private schools, which are better resourced and thus more capable of fostering AI integration (Okolo, 2019).

Despite growing discourse on AI in education, few empirical studies have examined secondary school students in semi-urban communities like Omoku. Existing research largely emphasizes national or urban contexts, leaving a gap in localized evidence on how infrastructural conditions, student preparedness, and school-type differences shape adoption outcomes. This absence of context-specific data raises critical questions about whether SS3 students in Omoku are adequately supported to integrate AI into their learning.

This study therefore addresses these empirical gaps by systematically examining three measurable dimensions: the availability of digital infrastructure, student readiness levels, and the influence of school type on AI adoption in Omoku. By grounding analysis in observable conditions and disparities, the findings aim to generate evidence-based insights into the prerequisites for equitable and effective AI integration in Nigerian secondary education.

Purpose of the study

This study seeks to understand the conditions that influence the adoption of AI technologies in the learning experiences of SS3 students in Omoku. Specifically, the study aims to:

1. Assess the availability of digital infrastructure that enables AI-based learning for SS3 students in Omoku.
2. Determine the readiness of SS3 students in Omoku to adopt AI technologies in their learning processes.
3. Examine the influence of school type (public or private) on the adoption of AI technologies among SS3 students in Omoku.

Research questions

The following research questions were formulated to guide this study:

1. What level of digital infrastructure is available to support AI-based learning for SS3 students in Omoku?
2. How prepared are SS3 students in Omoku to adopt AI technologies in their learning processes?
3. To what extent does school type (public or private) influence AI technology adoption among SS3 students in Omoku?

Hypotheses

The following null hypotheses are formulated for the study and are tested at a 0.05 level of significance.

H01: There is no significant difference between the mean score of responses on digital infrastructure availability and the benchmark mean score of 3.0.

H02: There is no significant difference between the mean score of responses on student readiness and the benchmark mean score of 3.0.

H03: There is no significant difference between the mean AI adoption scores of SS3 students in public schools and those in private schools in Omoku.

Significance of the Study

This study holds significant value as it will address a critical gap in understanding the factors that influence the adoption of AI technologies in secondary school education within semi-urban Nigerian settings, particularly in Omoku, in the following ways:

- The findings will contribute to educational policy and planning by offering evidence on the state of digital infrastructure in semi-urban schools. Policymakers will gain a clearer understanding of the resources required for effective AI implementation, enabling informed decisions regarding ICT investments and equitable distribution of technological facilities across public and private schools. This will support efforts to bridge the digital divide and promote inclusive learning environments.

- For school administrators, the study highlights practical areas for improvement, including internet accessibility, electricity stability, and the provision of digital devices. It also provides insights into student readiness, enabling the development of targeted training programs to enhance digital literacy and support AI-based learning initiatives.
- Teachers will benefit from a deeper understanding of students' preparedness for AI integration, allowing them to adopt more effective instructional strategies. Students, particularly those in SS3, will gain from improved learning experiences through personalized and adaptive AI tools, while also developing essential digital skills for future academic and career pursuits.
- Academically, the study contributes to existing literature by presenting a holistic analysis of digital infrastructure, student readiness, and school type as key determinants of AI adoption. Furthermore, it supports broader societal goals by promoting equitable access to technology, enhancing educational quality, and preparing students for active participation in a digitally driven economy.

Scope of the study

This study is delimited to Omoku, the administrative headquarters of ONELGA in Rivers State, Nigeria. It focuses specifically on SS3 students enrolled in both public and private secondary schools, who are at a critical stage of preparing for national examinations and transition into higher education. The investigation is bounded by three key dimensions: the state of digital infrastructure, the level of student readiness, and the influence of school type on AI adoption.

Review of Related Literature

Figure 1 presents a clear and structured overview of the foundational elements guiding this study; it illustrates the sequential flow of the research framework, capturing the four main thematic pillars: the Conceptual Framework, which outlines the key constructs under investigation; the Theoretical Framework, which anchors the study in established models of technology adoption and diffusion; the Related Empirical Review, which synthesizes prior research findings; and the Summary of Reviewed Literature, which consolidates insights and identifies gaps for further exploration.

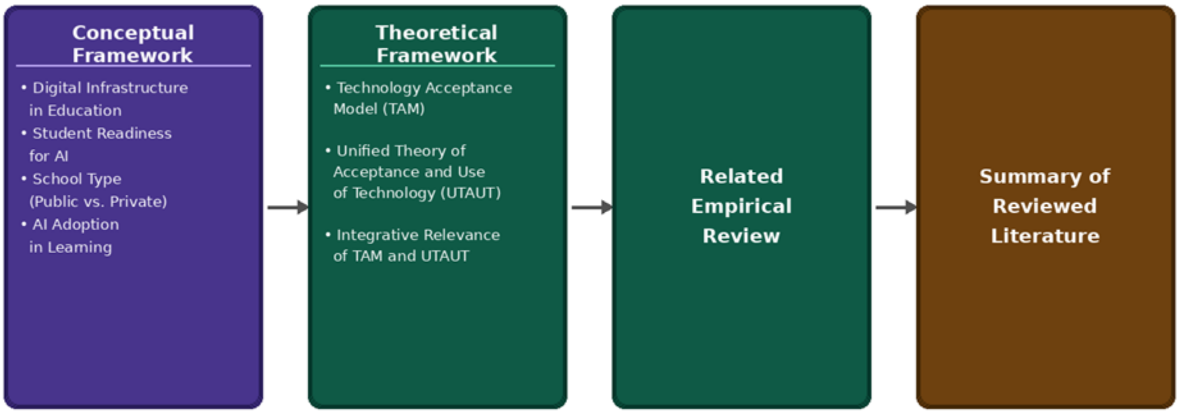

Figure 1: Sequential flowchart of the research framework

Conceptual Framework

The integration of AI in education has become one of the most transformative innovations in the 21st century. AI is reshaping how students learn, how teachers teach, and how schools operate. In the context of secondary education, particularly in developing nations like Nigeria, assessing students' readiness and perception toward AI is essential for determining how effectively technology can be adopted in the learning environment.

The conceptual framework illustrates that digital infrastructure forms the technological base for AI-driven learning, student readiness captures the skills and attitudes necessary for using AI, and the type of school determines resource availability; together, these factors influence how effectively SS3 students adopt AI.

Digital infrastructure in education

Digital infrastructure is the foundation for effective AI adoption in schools, especially for SS3 learners. Hardware availability, computers, tablets, and smartphones, ensures students can access intelligent tutoring systems, virtual assistants, and AI-based assessments. Without functional devices, engagement with these tools is limited. Connectivity is equally crucial: reliable broadband, Wi-Fi, or mobile networks (4G/5G) enable access to cloud-based AI platforms like ChatGPT, adaptive learning systems, and simulations. In rural and semi-urban areas, unstable networks hinder consistent use. Power supply also plays a decisive role. Frequent outages in Nigeria disrupt digital learning, making alternatives such as solar installations and inverters vital for continuity (Ukaoha et al., 2025). Finally, a supportive software ecosystem, Learning Management Systems, AI-enabled platforms, and licensed applications, creates the environment where AI tools can thrive. Together, these elements determine readiness for AI-driven education.

Student Readiness for AI

Readiness describes how prepared individuals are to engage with new technologies. For SS3 students adopting AI, readiness is multidimensional, involving skills, understanding, and psychological disposition. Digital literacy is a key component, covering the ability to operate devices, navigate software, and access online platforms. Without these skills, students struggle to use AI tools effectively. AI literacy extends further, requiring knowledge of AI's capabilities, limitations, and ethical concerns such as privacy, bias, and responsible use. This equips learners to critically evaluate AI outputs rather than depend on them blindly. Psychological readiness also matters, encompassing attitudes, motivation, perceived usefulness, and anxiety toward advanced tools. Research highlights a "knowledge-perception paradox," where students show enthusiasm for AI but lack deep understanding (David-Olawade et al., 2025). Addressing this gap demands targeted initiatives to build competence and confidence.

School type (public vs. private)

School type moderates AI adoption by shaping access to resources and learning conditions. In Nigeria, private schools benefit from stronger funding through tuition, donations, and private-sector investment, which supports modern ICT facilities, digital devices, stable internet, and faster integration of innovative technologies. Their autonomy in curriculum design allows quicker incorporation of AI-based tools, digital literacy programs, and personalized learning, aided by smaller class sizes (Ahunanya et al., 2025). Public schools, however, rely on government funding and often face underinvestment, resulting in poor ICT infrastructure, limited internet, low device-to-student ratios, and unstable electricity (Imiruaye & Christogonus-Anyanwu, 2024; Jacob & Dahir, 2021). Large student populations and bureaucratic delays further hinder reforms. Studies highlight challenges in policy implementation, teacher training, and infrastructure maintenance (Abubakar, 2016). These disparities make school type a crucial moderating factor in AI readiness.

AI adoption in learning

Adoption refers to the meaningful integration of AI technologies into SS3 students' learning experiences. True adoption goes beyond access to digital tools, emphasizing consistent and purposeful use in academics. A key dimension is personalized learning, where AI systems tailor content, pacing, and difficulty to individual needs, identify gaps, and provide immediate feedback, supporting preparation for exams like WAEC and NECO. Another aspect is research assistance: generative AI tools, such as chatbots and virtual assistants, help summarize materials, create study guides, clarify concepts, and foster information literacy. Additionally, AI supports administrative tasks like scheduling, assignment tracking, and personalized study plans. When fully adopted, AI enhances productivity, engagement, and performance, becoming a supportive partner in students' educational journey.

*Variable structure***:** Figure 2 illustrates the conceptual framework guiding this study. It shows how digital infrastructure enables access, student readiness enables use, and school type moderates conditions, all converging to determine AI adoption among SS3 students in Omoku.

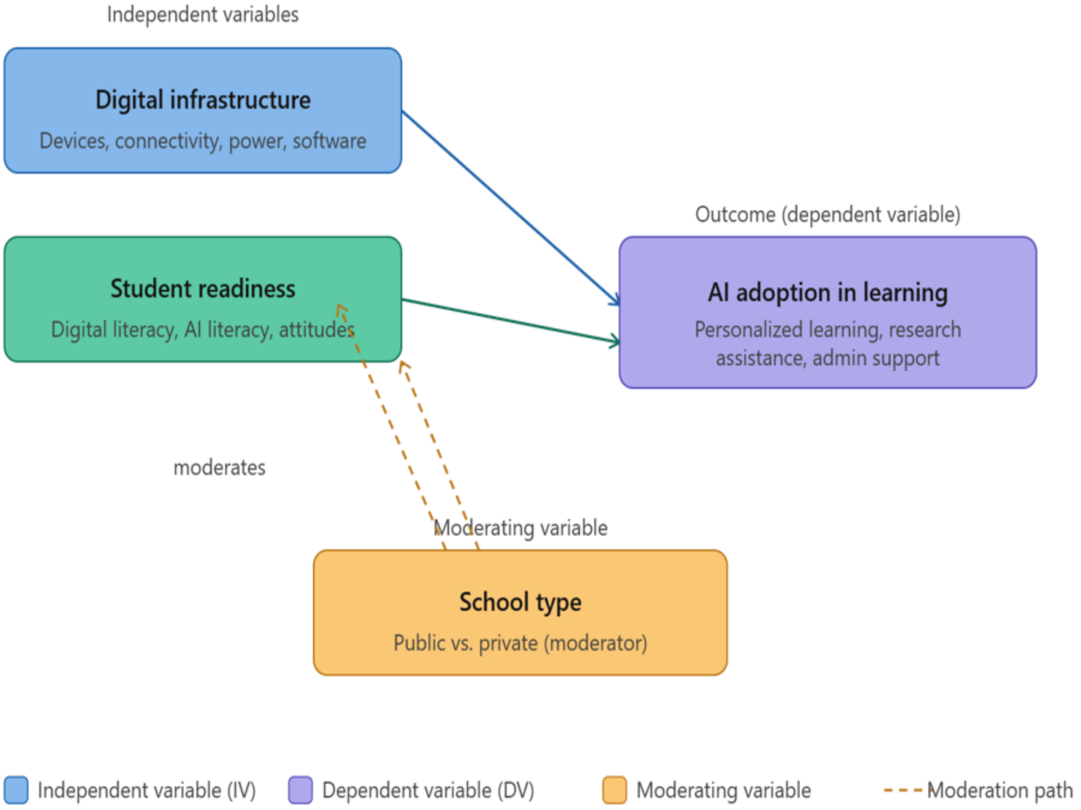

Figure 2: Conceptual Framework for AI Adoption in Learning

This study's conceptual framework establishes a structured relationship among digital infrastructure, student readiness, school type, and AI adoption in learning. Digital infrastructure and student readiness are the independent variables, each exerting a direct influence on the dependent variable – AI adoption among SS3 students. Digital infrastructure includes access to devices, internet connectivity, stable electricity, and functional software systems that enable students to interact with AI tools. Student readiness represents learners' cognitive and psychological preparedness, encompassing digital literacy, AI literacy, motivation, and attitudes toward technology. Both variables are theorized to independently predict the extent to which students integrate AI into their learning experiences.

School type functions as a moderating variable rather than a direct predictor. It shapes the strength and direction of the relationships between the independent and dependent variables. Given the disparities between public and private schools in Nigeria – particularly in funding, ICT infrastructure, and institutional support – the influence of digital infrastructure and student readiness on AI adoption is expected to vary across school types.

This moderated framework enhances theoretical clarity and methodological coherence. Conceptually, it recognizes that school type defines the context within which infrastructure and readiness operate. Methodologically, it aligns with the study's hypotheses, especially those examining differences in AI adoption across school types. By articulating this variable architecture, the framework provides a precise explanation of how these factors interact to produce AI adoption outcomes among senior secondary students in Nigeria.

Theoretical framework

This study is grounded in the Technology Acceptance Model (TAM), which explains how perceived usefulness and ease of use shape technology adoption, and the Unified Theory of Acceptance and Use of Technology (UTAUT), which highlights performance expectations, effort, social influence, and supporting conditions.

Technology acceptance model (TAM)

The Technology Acceptance Model (TAM), proposed by Davis (1989), explains that a user's decision to adopt new technology depends on two central beliefs: perceived usefulness and perceived ease of use. Perceived usefulness reflects the extent to which students believe AI can enhance learning outcomes, improve efficiency, or support exam preparation. When learners recognize clear academic benefits, such as faster research, personalized learning support, or better comprehension of difficult subjects, they are more likely to embrace AI tools. Perceived ease of use, on the other hand, refers to how simple and intuitive students find AI applications. If tools are accessible and require minimal technical skills, consistent usage becomes more likely.

In this study, both factors are shaped by digital infrastructure and student readiness. Inadequate resources, such as unstable internet, limited devices, or unreliable electricity, reduce ease of use. Similarly, low digital literacy weakens confidence and willingness to adopt AI. Thus, even when AI offers significant academic value, adoption among SS3 students in Omoku may remain limited unless these foundational barriers are addressed.

Unified theory of acceptance and use of technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh, Morris, Davis, and Davis (2003), expands earlier models by emphasizing that technology adoption depends not only on perceptions and attitudes but also on supportive environmental conditions. A key construct, facilitating conditions, refers to the technical, organizational, and infrastructural resources that enable technology use. In this study, facilitating conditions directly align with digital infrastructure. Even when students show strong motivation or confidence, adoption of AI tools is limited without reliable internet, steady electricity, functional devices, and supportive software systems.

This framework is particularly relevant when comparing public and private schools. Private schools typically provide stronger facilitating conditions due to better funding and investment in ICT resources, while public schools often struggle with infrastructural and administrative constraints. Consequently, differences in AI adoption across school types can be meaningfully explained through the lens of facilitating conditions.

Integrative relevance of TAM and UTAUT

The integrative relevance of the TAM and the UTAUT lies in their complementary ability to explain both individual and contextual determinants of AI adoption in education. TAM emphasizes students' perceptions of usefulness and ease of use, showing how attitudes and confidence shape willingness to engage with AI tools. However, these perceptions are often constrained by infrastructural realities such as unstable internet, limited access to devices, and irregular electricity supply. UTAUT extends this perspective by incorporating facilitating conditions, social influence, and performance expectations, thereby highlighting the role of environmental support and institutional differences, particularly between public and private schools, in shaping actual technology use. Together, TAM and UTAUT provide a holistic framework: while TAM captures the psychological and attitudinal readiness of SS3 students in Omoku, UTAUT situates these dispositions within broader structural and organizational contexts. This integration underscores that successful AI adoption requires not only positive student perceptions but also enabling infrastructural and institutional conditions, thereby offering a comprehensive explanation of technology acceptance in semi-urban Nigerian secondary schools.

Both TAM and UTAUT, despite their theoretical utility, present limitations that must be acknowledged in this study. TAM, emerged from organisational contexts where adult users made deliberate, voluntary choices about technology adoption. Its constructs, perceived usefulness and perceived ease of use, were framed around instrumental, task-oriented motivations. These assumptions may not adequately capture the exploratory, socially influenced, and emotionally driven engagement typical of adolescent learners. Similarly, UTAUT, was validated among adult employees in corporate environments. Its emphasis on performance expectancy, effort expectancy, and social influence reflects workplace utility rather than academic motivation or peer-driven behaviour in secondary schools. Although UTAUT2 later incorporated hedonic motivation and habit, these extensions were designed for consumer contexts rather than specifically for adolescent students in developing-country educational settings.

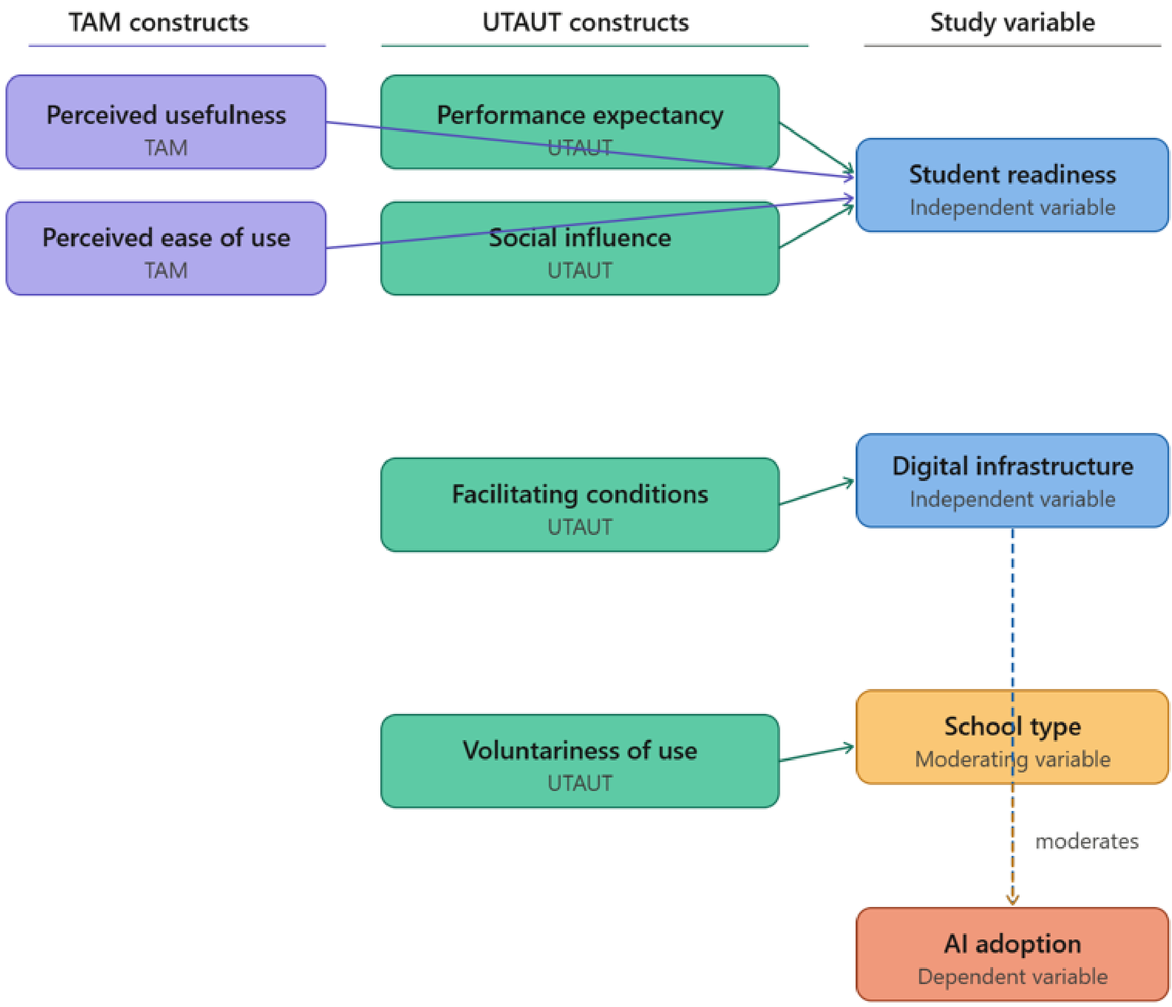

Figure 3: Theoretical construct mapping of TAM and UTAUT onto study variables

These limitations are particularly relevant in this study, which focuses on SS3 students in Omoku, a semi-urban community in Rivers State, Nigeria. Here, technology access is uneven, digital socialisation is largely informal, and institutional support for AI integration remains limited. To address these contextual gaps, TAM and UTAUT constructs were reinterpreted for school-age populations. Perceived usefulness was reframed to reflect students' beliefs about AI improving academic performance and exam preparation. Perceived ease of use was adapted to their confidence in navigating digital platforms within existing literacy levels. Facilitating conditions were redefined to include school-level infrastructure such as device availability, internet access, power supply, and software. Social influence was contextualised around teachers, peers, and parents rather than workplace supervisors. By reframing these constructs, this study extends TAM and UTAUT beyond organisational boundaries while remaining transparent about the theoretical adaptations made.

Figure 3 presents a visual mapping of TAM and UTAUT theoretical constructs onto the study variables. Perceived usefulness and ease of use from TAM, alongside performance expectancy, social influence, facilitating conditions, and voluntariness of use from UTAUT, are traced to their corresponding independent, moderating, and dependent variables, illustrating the framework's theoretical lineage.

Related Empirical Review

Several studies underscore the persistent infrastructural barriers to ICT integration in schools. Asuquo et al. (2023) identified poor literacy, high costs, weak connectivity, and unreliable power supply as major obstacles in Kwara State. Malima et al. (2023) similarly found that while basic digital skills supported teaching in Tanzania, inadequate infrastructure, internet access, and training limited adoption. Asaolu & Fashanu (2012) and Adeoluwa et al. (2013) reported deficits in ICT facilities across Lagos and Ondo States, with funding and resource shortages constraining uptake despite positive attitudes among stakeholders. Guobadia & Ekuobase (2024) quantified these disparities through the Digital Learning Culture Index (DLCI = 0.21), revealing systemic inequalities and regional gaps. Collectively, these studies highlight the need for investment in infrastructure, reliable connectivity, and sustained funding to enable effective technology use.

Evidence suggests that students generally demonstrate readiness and positive dispositions toward digital learning. Karami (2024) found AFIT undergraduates prepared for digital classrooms, though challenges persisted. Ife-Abodunrin & Roseline (2025) reported favorable attitudes among Lagos State students, with no gender differences, while Nuezca et al. (2024) showed strong digital literacy and readiness among Science and Math students, with ICT skills and information literacy emerging as key predictors of adoption. These findings indicate that students are willing and capable of engaging with digital tools, provided adequate support and integration into curricula.

Studies also examined the determinants of adoption beyond infrastructure. Karan & Angadi (2025), using the TOE framework, demonstrated that technological, organizational, and environmental factors strongly influence AI readiness among secondary students. Varzaru & Ghita (2025), applying TAM, found behavioral intention to be the strongest driver of adoption among Romanian teachers, with ease of use outweighing perceived usefulness. This suggests that intuitive tools, supportive environments, and teacher training are critical for sustained uptake. Asaolu & Fashanu (2012) further emphasized disparities between public and private schools, where resource availability shaped adoption outcomes.

Despite the expanding scholarship on digital technology integration and AI adoption in secondary education, a clear geographical and contextual gap remains. Nigerian studies on ICT adoption and digital readiness have largely focused on urban centres such as Lagos (Ife-Abodunrin & Roseline, 2025; Asaolu & Fashanu, 2012) and state capitals like Ilorin in Kwara State (Asuquo et al., 2023) and Akure in Ondo State (Adeoluwa et al., 2013), where infrastructure and institutional support are comparatively stronger. National-level studies, including Guobadia & Ekuobase (2024), aggregate findings across regions without isolating semi-urban realities. To the researcher's knowledge, no empirical work has examined how digital infrastructure, student readiness, and school type jointly influence AI adoption in Omoku or similar semi-urban communities in Rivers State. This absence is significant because semi-urban contexts occupy a middle ground between rural underservice and urban advantage, marked by uneven infrastructure, mixed public-private school representation, and varied student digital exposure. Addressing this gap, the present study contributes original, context-specific evidence to the literature on AI adoption in Nigerian secondary education.

Summary of Reviewed Literature

Across the reviewed studies, three converging themes emerge. First, infrastructural deficits – encompassing unreliable internet connectivity, inadequate devices, erratic power supply, and insufficient institutional support – consistently represent the most significant barrier to digital technology and AI adoption in secondary education, a pattern documented across Nigerian, Tanzanian, and Romanian contexts alike. Second, students generally demonstrate positive attitudes and baseline readiness toward digital learning, though readiness is uneven and often contingent on the quality of prior digital exposure and the availability of enabling school environments. Third, actual adoption is most strongly predicted by perceived ease of use, behavioural intention, and the presence of supportive organisational and infrastructural conditions, suggesting that attitudinal readiness alone is insufficient without corresponding structural enablers.

Omoku, a semi-urban community in Rivers State, presents unique conditions for studying AI adoption among SS3 students. Unlike urban centres or international contexts examined in prior research, Omoku's digital infrastructure is uneven, and public and private schools operate under starkly different resource environments. Students here prepare for high-stakes national examinations in circumstances not directly addressed in existing literature. This study therefore fills a critical gap by investigating how infrastructural limitations and institutional disparities shape the relationship between student readiness and AI adoption. Rather than replicating earlier inquiries, it generates context-specific evidence that can guide policy interventions and school-level strategies tailored to semi-urban Nigerian communities where technology adoption remains distinct and underexplored.

Methodology

The step-by-step methodological processes that were employed in this study are visually presented in the flowchart in Figure 4.

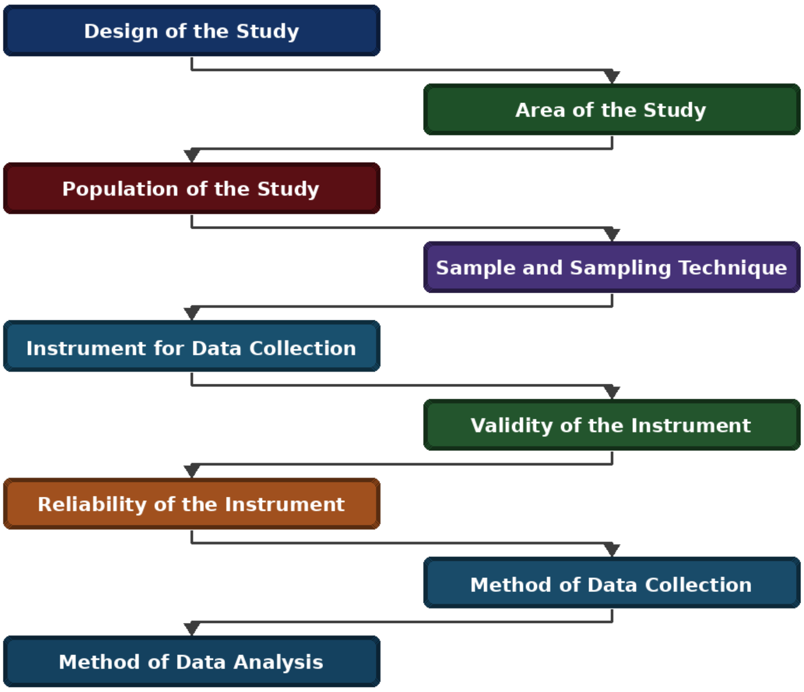

Figure 4: Methodological flow chart

Design of the study

This study employed a descriptive survey research design to examine perceptions, readiness, 3and infrastructural factors influencing AI adoption among SS3 students in Omoku. The design was deemed suitable because it facilitates the systematic collection and analysis of data from a clearly defined population without altering or manipulating study variables. This approach aligns with the methodological guidance of Creswell (2014) and Ejimaji & Ellah (2014), who emphasize the appropriateness of such designs for studies that seek to observe and interpret phenomena as they naturally occur.

Area of the study

Omoku, the study area, is a semi-urban community in Rivers State with an estimated population of 320,000, according to the 2006 Nigerian census (National Population Commission, 2026). It serves as the headquarters of Ogba/Egbema/Ndoni Local Government Area (ONELGA) and hosts a mix of public and private schools, alongside tertiary institutions such as the Federal College of Education (Technical), Omoku, making it a relevant educational hub for examining technology adoption among students.

Population of the study

The study population consisted of all SS3 students enrolled in both public and private secondary schools in Omoku. A total of 1,013 students were included, drawn from three public and seventeen private schools.

Sample and sampling technique

To derive a representative sample capable of ensuring reliable statistical inference at a 95% confidence level with a 5% margin of error, this study utilized the finite population formula developed by Taro Yamane. According to Ejimaji & Ellah (2014), Yamane (1967), and Israel (1992), this technique is widely employed in survey research to determine appropriate sample sizes from known populations while maintaining acceptable levels of sampling precision:

$$n = \frac{N}{1+N(e)^2} \qquad (1)$$

In this context, (n) represents the sample size, (N) is the population size (1,013), and (e) denotes the level of precision or margin of error (0.05). The calculated sample size (n) was 287, and the average response rate for the questionnaires was 83.6%.

A stratified sampling technique with proportional allocation was adopted in this study to guarantee that the sample mirrored the relative distribution of SS3 students across the 20 schools (treated as strata). This method reduced sampling bias and improved the precision of population estimates. The sample size for each stratum was calculated using the proportional allocation formula:

$$nh = n\frac{Nh}{N} \qquad (2)$$

Where: nh = sample size for stratum h, n = total sample size (287), Nh = population size of stratum h, N = total population size (1,013).

Instrument for data collection

A structured questionnaire developed by the researcher, titled "Questionnaire on Digital Infrastructure, Student Readiness, and School Type Influence on AI Adoption in Learning (AAS), was utilized. The instrument was specifically designed to assess three core variables: availability of digital infrastructure, student readiness, and differences based on school type.

The questionnaire items were organized on a five-point Likert scale ranging from Strongly Disagree (1) to Strongly Agree (5): Strongly Agree (SA) – Agree (A) – Neither Agree nor Disagree (N) – Disagree (D) – Strongly Disagree (SD), allowing respondents to express varying levels of agreement. The responses were analyzed using mean scores to enable comparison across the different variables, with interpretations guided by the following benchmarks: mean values below 3.0 indicated low or inadequate levels, scores between 3.0 and 3.49 reflected moderate or fair levels, values from 3.50 to 3.99 suggested moderate to high levels, and scores of 4.0 or above represented high or strong levels. According to Koo & Yang (2025), these cut-offs are grounded in the midpoint logic of a 5-point Likert scale, where 3.0 signifies a neutral threshold, serving as a logical dividing point between lower and higher levels of perception or agreement. In addition, hypotheses were tested at the 0.05 level of significance, ensuring that the evaluation of AI adoption among SS3 students in Omoku was systematic, reliable, and valid.

Validity of the Instrument

To ensure validity, both face and content validation procedures were employed. The questionnaire was developed through an extensive review of existing literature and standardized instruments on digital literacy and AI adoption, thereby aligning with established theoretical constructs. Expert reviewers provided feedback during the validation process, leading to revisions of four items, the removal of two items, and the addition of three new items. While face and content validity offered initial refinement, construct validity was further reinforced by adapting items from previously validated instruments. The experts' evaluations, including corrections and suggestions, helped refine the instrument by ensuring clarity, relevance, and adequate coverage of all study variables. This process significantly enhanced the credibility and accuracy of the questionnaire.

Reliability of the instrument

To establish the reliability of AAS, Cronbach's Alpha coefficient was computed using the standard Cronbach formula. This statistical measure evaluated the internal consistency of the instrument.

The reliability analysis was based on data obtained from a pilot study involving SS3 students drawn from schools outside the main study sample. The pilot dataset comprised responses to

22 Likert-scale items, each rated on a five-point scale (1–5). The data were coded and entered into the Statistical Package for the Social Sciences (SPSS) for analysis.

Within SPSS, item variances and total scale scores were computed, and these values were subsequently applied in Cronbach's Alpha formula as presented in Equation (3). The reliability analysis was conducted for each section of the instrument, Section B (Digital Infrastructure), Section C (Student Readiness), and Section D (AI Adoption, Private vs. Public schools), as well as for the overall 22-item instrument.

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\Sigma\sigma_{item}^2}{\sigma_{total}^2}\right) \quad (3)$$

Where k is the number of items, $\Sigma\sigma_{item}^2$ is the sum of item variance and σ_{total}^2 is the variance of the total score.

Reliability was assessed for each section of the instrument, Section B (Digital Infrastructure), Section C (Student Readiness), and Section D (AI Adoption across private and public schools), as well as for the overall 22-item instrument. The resulting Cronbach's alpha coefficients are reported: The AAS demonstrated excellent internal consistency across all three subscales (α = 0.927–0.964) and good overall reliability (α = 0.837). These values exceed the widely accepted thresholds of 0.70 (acceptable) and 0.80 (good) recommended by Nunnally & Bernstein (1994) and George & Mallery (2020). While the very high subscale alphas may partly reflect item homogeneity, they nonetheless confirm that items within each construct measure the same underlying dimension with minimal random error. The slightly lower overall alpha is expected and acceptable given the multidimensional nature of the instrument. No item deletion improved reliability, further confirming that all items are psychometrically sound. Accordingly, the instrument is considered highly reliable for use in the main study and suitable for application in similar semi-urban Nigerian secondary school contexts.

Method of Data Collection

Data collection followed a structured and ethically sound procedure. Formal permission was obtained from the respective school authorities prior to administration. Ethical approval for the study was granted by the Project Seminar Committee of the Federal College of Education (Technical), Omoku. In addition, respondents were clearly informed about the purpose of the study, their rights, and the confidentiality of their responses, ensuring transparency and voluntary participation throughout the process. The questionnaires were administered face-to-face, with the researcher and three trained research assistants supervising the process. This arrangement allowed for clarification when needed and ensured that responses were properly completed.

Method of Data Analysis

The data collected were analyzed using both descriptive and inferential statistical techniques with the aid of IBM SPSS Statistics version 25. Descriptive statistics, specifically the mean, were computed to address the three research questions by summarizing the respondents' perceptions of digital infrastructure availability, student readiness for AI adoption, and the level of AI technology adoption. For each school and each section of the instrument, a mean score was computed using the formula:

$$\overline{x}_s = \frac{(5\times f_{SA}) + (4\times f_A) + (3\times f_N) + (2\times f_D) + (1\times f_{SD})}{N} \quad (4)$$

Where:33

$\overline{x}_s$ = mean score for school "s" on a given section of the questionnaire

f_{SA}, f_A, f_N, f_D, f_{SD} = frequency of responses in the Strongly Agree, Agree, Neither Agree nor Disagree, Disagree, and Strongly Disagree categories respectively.

N= total number of responses for that school and section, where N=f_{SA} + f_A + f_N + f_D + f_{SD}

Group mean scores were subsequently computed by averaging the individual school means across school type. The private school mean ($\overline{x}_{private}$) was derived from the seventeen (17) private schools sampled, while the public-school mean ($\overline{x}_{public}$) was derived from the three (3) public schools. The overall mean ($\overline{x}_{overall}$) was computed across all twenty (20) schools as follows:

$$\overline{x}_{overall} = \frac{\overline{x}_1 + \overline{x}_2 + \ldots + \overline{x}_{20}}{20} \quad (5)$$

This analytical framework was applied consistently across the three research questions, generating the mean scores reported in Tables 2, 4, and 6 of the results and discussion of results section.

Inferential statistics were used to test the three null hypotheses at a 0.05 significance level. One-sample t-tests assessed whether the mean scores for digital infrastructure availability and student readiness differed significantly from the benchmark mean of 3.0, representing an adequate level on the 5-point scale. An independent-samples t-test compared mean AI adoption scores between students from public and private schools.

Prior to conducting these tests, assumptions of normality and homogeneity of variance were examined. Normality was assessed using the Shapiro–Wilk test, which indicated that the distributions of mean scores did not significantly deviate from normality ($p > 0.05$). For the independent-samples t-test, Levene's test for equality of variances was performed; results showed that the assumption of homogeneity was met ($p > 0.05$). Since all assumptions were satisfied, standard parametric tests were applied. Decisions to reject or accept each null hypothesis were based on p-values, with $p \leq 0.05$ indicating rejection and $p > 0.05$ indicating acceptance.

Results and Discussion

Research Questions:

Research Question 1 (RQ1): What level of digital infrastructure is available to support AI-based learning for SS3 Students in Omoku?

Table 1: Per-school mean scores (Section B) – Digital infrastructure

S/No.	School	Type	Section B means
1.	Becky academy	Private	3.82
2.	Bolym wisdom academy	Private	3.71
3.	Ellah international school	Private	3.78
4.	Fantastic international academy	Private	3.83
5.	Gifted chosen model school	Private	3.83
6.	Goshen comprehensive college	Private	3.84
7.	Hallmark academy	Private	3.68
8.	Immaculate comprehensive college	Private	3.68
9.	Provil school	Private	3.95
10.	Seat of greatness international	Private	3.59
11.	Sunshine academy	Private	3.66
12.	Kings comprehensive group of schools	Private	3.69
13.	Ogba comprehensive group of schools	Private	3.61
14.	Cambridge paradise school	Private	3.63
15.	3rd Tier academy	Private	3.89
16.	Saint Mary’s catholic school	Private	3.86
17.	Beautiful cannanland	Private	3.93
18.	Model boys secondary school	Public	2.29
19.	Community girls secondary school	Public	2.34
20.	Community secondary school	Public	2.36

Table 1 presents the mean scores for Section B (Digital Infrastructure) across schools. Table 2 summarizes the overall mean scores for the Digital Infrastructure construct, derived from the school-level results in Table 1. It shows that the overall mean score of 3.30 reflects a moderate level of digital infrastructure availability, slightly exceeding the Likert benchmark mean of 3.0.

However, there is a notable disparity between school types. Private schools have a mean score of 3.76, indicating a moderate-to-high level of infrastructure, whereas public schools score only 2.34, below the benchmark.

Table 2: Overall mean scores of digital infrastructures

Aspect	Overall mean score	Private school mean	Public school mean	Standard deviation	Interpretation
Availability of Digital Infrastructure for AI Learning (RQ1)	3.30	3.76	2.34	0.55	Moderate

Research Question 2 (RQ2): How prepared are SS3 students in Omoku to adopt AI technologies in their learning processes?

Table 3: Per-school mean scores (Sections C) – Student readiness

S/No.	School	Type	Section C means
1.	Becky academy	Private	3.40
2.	Bolym wisdom academy	Private	3.63
3.	Ellah international school	Private	3.54
4.	Fantastic international academy	Private	3.51
5.	Gifted chosen model school	Private	3.42
6.	Goshen comprehensive college	Private	3.47
7.	Hallmark academy	Private	3.60
8.	Immaculate comprehensive college	Private	3.25
9.	Provil school	Private	3.44
10.	Seat of Greatness International	Private	3.47
11.	Sunshine academy	Private	3.58
12.	Kings comprehensive group of schools	Private	3.49
13.	Ogba comprehensive group of schools	Private	3.34
14.	Cambridge paradise school	Private	3.20
15.	3rd Tier Academy	Private	3.30
16.	Saint Mary catholic school	Private	3.56
17.	Beautiful Cannanland	Private	3.75
18.	Model Boys secondary school	Public	3.27
19.	Community Girls secondary school	Public	3.30
20.	Community secondary school	Public	3.22

Table 4: Overall Mean Scores of Student Readiness

Aspect	Overall mean score	Private school mean	Public school mean	Interpretation
Student readiness to adopt AI technologies (RQ2)	3.39	3.45	3.25	Moderate

Table 3 presents the mean scores for Section C (Student Readiness) for each school. Table 4 provides the overall mean score for the Student Readiness construct, derived from the school-level results in Table 3. In Table 4, the overall mean score of 3.39 indicates that students have a moderate level of readiness to adopt AI technologies, slightly above the 3.0 Likert average. Private school students scored 3.45, while public school students scored 3.25, with both groups falling within the moderate range.

Research Question 3 (RQ3): To what extent does school type (public or private) influence AI technology adoption among SS3 students in Omoku?

Table 5: Per-school mean scores (Sections D) AI adoption

S/No.	School	Type	Section D Means
1.	Becky academy	Private	4.44
2.	Bolym wisdom academy	Private	3.72
3.	Ellah international school	Private	3.56
4.	Fantastic international academy	Private	3.57
5.	Gifted chosen model school	Private	3.46
6.	Goshen comprehensive college	Private	3.67
7.	Hallmark academy	Private	3.34
8.	Immaculate comprehensive college	Private	3.40
9.	Provil school	Private	3.50
10.	Seat of Greatness International	Private	3.55
11.	Sunshine Academy	Private	3.51
12.	Kings Comprehensive Group of Schools	Private	3.63
13.	Ogba Comprehensive Group of Schools	Private	3.43
14.	Cambridge Paradise School	Private	3.70
15.	3rd Tier Academy	Private	3.71
16.	Saint Mary Catholic School	Private	3.71
17.	Beautiful Cannanland	Private	3.27

18.	Model Boys Secondary School	Public	3.17
19.	Community Girls Secondary School	Public	3.00
20.	Community Secondary School	Public	3.13

Table 6: Mean scores of AI adoption across public and private secondary schools in Omoku

Aspect	Overall mean score	Private school mean	Public school mean	Interpretation
Adoption of AI technologies in learning – private vs. public schools (RQ3)	3.39	3.53	3.09	Moderate

Table 5 presents the mean scores for Section D (AI Adoption) across schools. Table 6 reports the overall mean scores for the AI Adoption construct, calculated from the school-level results in Table 5. It shows an overall mean score of 3.39, indicating a moderate level of AI technology adoption, which surpasses the 3.0 benchmark mean. However, the level of adoption varies by school type. Private schools reported a score of 3.53 (moderate to high), while public schools had a score of 3.09 (moderate).

Visualization of overall mean scores by research questions

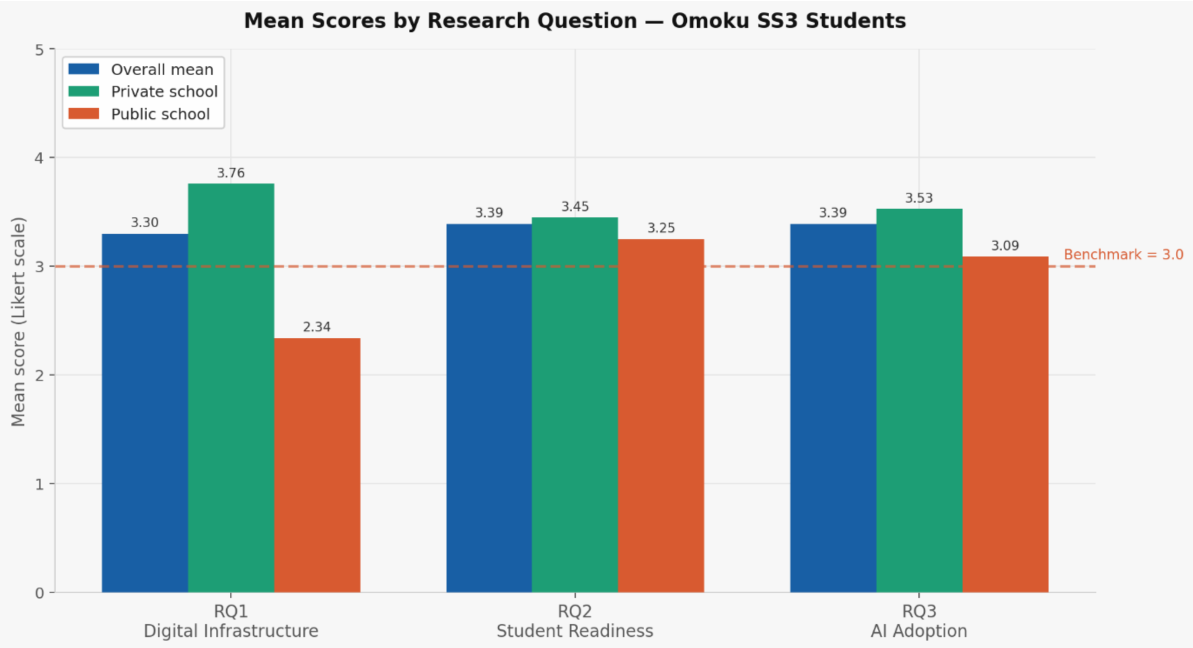

Figure 5: Mean scores by research questions

Figure 5 illustrates the mean scores for the three research questions. Across all categories, private schools record the highest mean scores, followed by the overall mean, while public schools consistently show the lowest values. All overall means are above the benchmark of 3.0, indicating generally positive perceptions. However, public schools fall notably below the benchmark in digital infrastructure and only marginally exceed it in student readiness and AI adoption. The largest disparity appears in Digital Infrastructure, highlighting a notable gap between private and public schools. Cumulatively, the figure underscores variations in access, preparedness, and adoption levels across school types.

Empirical insight

The results presented in Tables 2, 4 and 6, together with Figure 5, highlight important insights into digital infrastructure, student readiness, and AI adoption among SS3 students in Omoku. For Research Question 1 (RQ1), Table 2 shows an overall mean score of 3.30, indicating a moderate level of digital infrastructure availability. However, a sharp divide exists between private schools (M = 3.76) and public schools (M = 2.34), with the latter falling below the benchmark of 3.0. This suggests that while private schools are relatively well-equipped, public schools face consequential infrastructural challenges.

Research Question 2 (RQ2) examined student readiness. Table 4 reports an overall mean of 3.39, slightly above the benchmark, reflecting moderate preparedness. Both private (M = 3.45) and public (M = 3.25) schools scored within the moderate range, with only a modest difference between them. This implies that readiness levels are fairly consistent across school types, though private schools still hold a slight advantage.

For Research Question 3 (RQ3), Table 6 reveals an overall mean of 3.39 for AI adoption, again above the benchmark. Private schools scored 3.53, indicating moderate-to-high adoption, while public schools scored 3.09, reflecting moderate but lower adoption.

Figure 5 visually reinforces these findings with differing bar heights in the various construct, showing that private schools consistently outperform public schools across all three dimensions. The largest disparity appears in digital infrastructure, underscoring the critical role of resources in shaping AI adoption.

Overall, the findings reveal that while SS3 students in Omoku generally perceive digital infrastructure, readiness, and AI adoption positively, considerable disparities persist between public and private schools. Private schools consistently outperform their public counterparts across all three dimensions, with the sharpest divide evident in infrastructure availability. Although student readiness appears moderately strong and relatively consistent across school types, adoption levels remain uneven, reflecting the influence of resource gaps on implementation. The visual evidence further reinforces these patterns, underscoring that infrastructural inequality is the most critical barrier to equitable AI integration. Collectively, the results highlight both the promise of student motivation and the pressing need for targeted interventions to address systemic resource disparities if AI adoption is to be inclusive and sustainable across Nigeria's secondary schools.

Hypothesis

Hypothesis 1 (H1): There is no significant difference between the mean score of responses on digital infrastructure availability and the benchmark mean score of 3.0.

Table 7: One-sample t-test analysis of digital infrastructure availability for AI-based learning among SS3 students in Omoku.

H	Test type	M(SD)	Test value	t(df)	p-value	Decision
H1	One-sample t-test	3.30 (0.96)	3.00	$t(239) = 4.84$	$p < .001$	Reject H1

Table 7 presents one-sample t-test conducted on 240 valid responses (df = 239). The mean score for digital infrastructure availability (M = 3.30, SD = 0.96) was significantly higher than the test value of 3.00, $t(239) = 4.84$, $p < .001$. Therefore, H01 was rejected.

Hypothesis 2 (H2): There is no significant difference between the mean score of responses on student readiness and the benchmark mean score of 3.0.

Table 8: One-sample t-test analysis of SS3 students' readiness for AI technology adoption compared to the benchmark mean

H	Test type	M(SD)	t(df)	p-value	Decision
H2	One-sample t-test	3.39 (0.87)	$t(239) = 6.96$	$p < .001$	Reject H2

Table 8 presents A one-sample t-test conducted on 240 valid responses (df = 239). The mean score for student readiness (M = 3.39, SD = 0.87) was significantly higher than the benchmark mean of 3.00, $t(239) = 6.96$, $p < .001$. Therefore, H02 was rejected.

Hypothesis 3 (H3): There is no significant difference between the mean AI adoption scores of SS3 students in public schools and those in private schools in Omoku.

Table 9: Independent samples t-test analysis of the influence of school type (public vs. private) on AI technology adoption among SS3 students in omoku

H	Test type	M (SD) private	M (SD) public	t(df)	p-value	Decision
H3	Independent t-test	3.53 (Pooled SD=1.38)	3.09 (Pooled SD=1.38)	t(238) = 3.48	p = .001	Reject H3

Table 9 shows an independent samples t-test conducted to examine differences in AI adoption between SS3 students in private and public schools. Results showed that private school students (M = 3.53, SD = 1.38) reported significantly higher adoption scores compared to public school students (M = 3.09, SD = 1.38), t(238) = 3.48, p = .001. Therefore, H03 was rejected.

Visualization of observed t-values vs. significance and p-values vs. significance

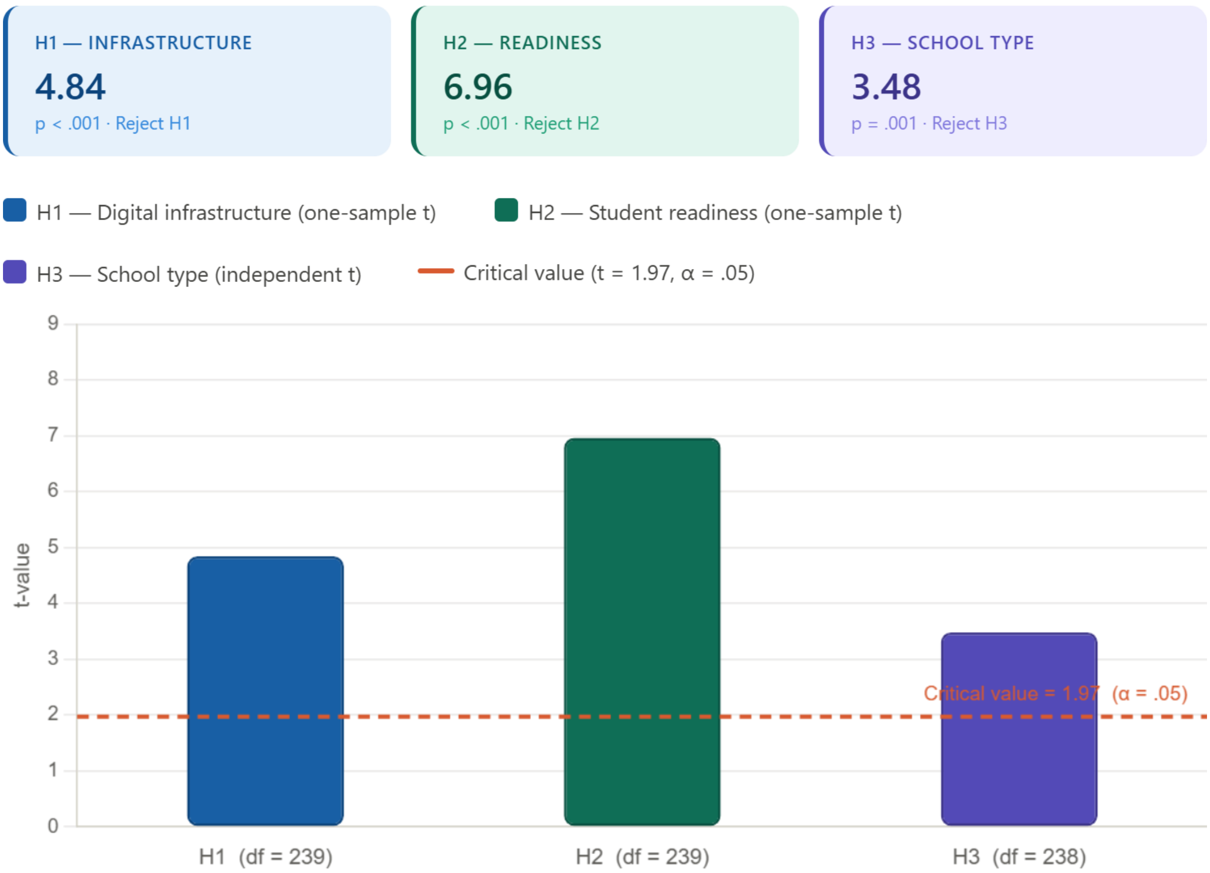

Figure 6: Observed t-values vs. significance

Figure 6 presents a bar chart comparing the observed t-statistics for three null hypotheses (H1, H2, and H3) against the critical t-value of 1.97 (α = .05, two-tailed). The blue bar representing H1 (digital infrastructure availability) shows an observed t-value of 4.84, the green bar for H2 (student readiness) records the highest t-value of 6.96, and the purple bar for H3 (school type differences) yields a t-value of 3.48. All three observed t-statistics notably exceed the critical threshold of 1.97, indicated by the dashed coral line, confirming that each null hypothesis was rejected at $p \leq .001$. This pattern suggests that digital infrastructure availability, student readiness, and school type each considerable influence AI technology adoption among SS3 students in Omoku.

Figure 7: P-values vs. significance

Figure 7 presents a bar chart displaying the p-values for all three null hypotheses on a logarithmic scale, plotted against the significance threshold of $\alpha = 0.05$, represented by the red dashed line. The blue bar for H1 (digital infrastructure availability) and the green bar for H2 (student readiness) both record p-values below .001, while the purple bar for H3 (school type differences) yields $p = .001$. On the logarithmic scale, all three bars fall dramatically below the red threshold line, providing compelling visual evidence that none of the results occurred by chance. These findings confirm that digital infrastructure availability, student readiness, and school type each exert a statistically substantial influence on AI technology adoption among SS3 students in Omoku.

Empirical insight

The results presented in Tables 7, 8, and 9, alongside Figures 6 and 7, provide strong evidence of statistically substantial findings across all three hypotheses. For H1, the one-sample t-test compared the mean score of digital infrastructure availability (M = 3.30) against the benchmark of 3.0. With a t-value of 4.84 and $p < .001$, the null hypothesis was rejected, indicating that students perceived digital infrastructure availability as noteworthy above average (Table 7).

Similarly, H2 examined student readiness for AI adoption. The mean score of 3.39 was significantly higher than the benchmark of 3.0, with a t-value of 6.955 and $p < .001$ (Table 8). This suggests that SS3 students demonstrated readiness levels well above the neutral threshold. Hypothesis H3 explored differences in AI adoption between public and private schools. The independent-samples t-test revealed that private school students (M = 3.53) scored meaningfully higher than public school students – M = 3.09, SD = 1.38), $t(238) = 3.48$, $p = .001$ (Table 9). This highlights a disparity in adoption levels based on school type.

Figures 6 and 7 visually reinforce these findings. Figure 6 shows all observed t-values exceeding the critical threshold of 1.97, confirming its statistical robustness. Figure 7 demonstrates that all p-values fall far below $\alpha = 0.05$ line, further validating the rejection of all null hypotheses. Taken together, the results provide robust empirical support for all three hypotheses, demonstrating that digital infrastructure availability, student readiness, and school type substantially shape AI adoption among SS3 students in Omoku. The one-sample t-tests confirmed that both infrastructure (M = 3.30) and readiness (M = 3.39) were perceived as considerable above the neutral benchmark, while the independent–samples t-test revealed a clear disparity between private and public schools in adoption levels. The visual evidence from Figures 6 and 7 further reinforced these findings, with all observed t-values exceeding critical thresholds and all p-values falling well below the $\alpha = 0.05$ line. Collectively, these results underscore that while students are motivated and moderately prepared for AI integration, structural inequalities in infrastructure, particularly between public and private schools-remain a decisive factor in shaping adoption outcomes.

Implications of the study

The findings of this study have important policy implications. The persistent digital divide between public and private schools highlights the urgent need for targeted interventions in semi-urban Nigerian contexts. Infrastructure deficits in public schools, such as unreliable electricity and limited internet access, continue to constrain AI adoption and exacerbate educational inequalities. Policymakers must therefore prioritize equitable resource allocation and establish enforceable standards to ensure that all schools, regardless of type, are adequately equipped to participate in the digital transformation of education.

From a practice perspective, the study emphasizes that while student readiness and attitudes toward AI are generally positive, these strengths are undermined by structural barriers. Teachers and students require sustained training in AI literacy and digital skills to translate motivation into effective integration. Schools should therefore adopt capacity-building initiatives that empower both educators and learners to use AI tools productively, even in resource-constrained environments.

Recommendations

Based on the findings of the study, the following recommendations aim to enhance digital readiness and overall system performance:

- Public–private partnerships: Policymakers should prioritize public–private partnerships to invest in public school digital infrastructure, such as solar-powered labs, subsidized internet, and devices, to bridge the adoption gap.
- Capacity building in AI literacy: Schools should implement teacher and student training programs focused on AI literacy and digital skills to build on existing student motivation and improve readiness for AI integration.
- Policy standards to reduce disparities: The Rivers State Ministry of Education should establish and enforce a minimum ICT provisioning standard for all approved secondary schools. This would ensure equitable resource allocation, systematic monitoring, and reduce disparities between public and private institutions, thereby promoting inclusive AI adoption.

Limitations of the study

This study is constrained by limitations that must be acknowledged:

- Geographic scope: The study was limited to SS3 students in Omoku, a semi-urban area, restricting generalizability to urban or rural regions of Nigeria or other educational contexts.
- Benchmark: The one-sample benchmark mean of 3.0 used as the threshold for “adequate” infrastructure or readiness is somewhat arbitrary, as it was not empirically derived from Nigerian school data. This raises a construct validity issue, since the

benchmark may not fully capture the realities of Nigerian secondary schools. Consequently, interpretations of adequacy based on this cut-off should be treated with caution.

- School approval bias: Only schools approved by the Rivers State Ministry of Education were included, excluding unapproved institutions and potentially introducing selection bias.
- Sample imbalance: The sample was heavily skewed toward private schools (17 out of 20), with 67.8% of students from private institutions. This imbalance limits the representativeness of public-school experiences.
- Generalizability concerns: Findings may not fully capture the diversity of public-school realities, so caution is needed when extrapolating results to the wider population.

Directions for Future Research

In view of these limitations, future research should consider:

- Balanced sampling: Ensure more equitable representation of public and private schools to strengthen external validity.
- Longitudinal studies: Employ longitudinal designs to track sustained effects of AI interventions on student learning outcomes over time.
- Moderating variables: Investigate factors such as gender, socioeconomic status, and regional differences to better understand variations in AI adoption.
- Comparative studies: Replicate the study in rural and urban areas of Rivers State to assess whether findings hold across the rural–urban continuum.
- Structural modelling: Test whether TAM/UTAUT constructs (perceived usefulness, ease of use, facilitating conditions) can be measured directly among Nigerian SS3 students, moving beyond proxy variables toward structural modelling of AI adoption.

Conclusion

This study explored the readiness, attitudes, and infrastructural realities shaping AI adoption among SS3 students in Omoku, Nigeria, using the TAM and the UTAUT as guiding frameworks. The findings affirm TAM’s central claim that perceived usefulness and ease of use influence willingness to adopt technology. Students demonstrated moderate readiness (mean 3.39) and positive attitudes toward AI, indicating psychological predispositions consistent with TAM’s predictions. However, the study also reveals TAM’s limitation: positive perceptions alone do not guarantee adoption when infrastructure is lacking. In contexts like

Omoku, where access is uneven, readiness remains latent rather than actionable, highlighting TAM's assumption of reliable technological access as a structural blind spot.

UTAUT provided a more comprehensive lens by emphasizing facilitating conditions and social influence. The study confirms these constructs as critical in semi-urban Nigeria. Infrastructure availability averaged 3.30, but disparities between school types were stark: public schools scored 2.34 compared to 3.76 in private schools. This inequality directly shaped adoption outcomes, with private school students reporting higher AI engagement (mean 3.53) than their public-school peers (mean 3.09). The rejection of all hypotheses, including the significant effect of school type, underscores UTAUT's insistence that environmental and organizational conditions are central determinants of technology use.

Together, the findings extend both models by exposing a structural asymmetry in Global South contexts: psychological readiness is decoupled from infrastructural enablement. Students are willing, but conditions are wanting. This suggests that technology adoption theory must adapt to resource-constrained environments by foregrounding institutional inequality and infrastructural deficits as primary explanatory variables. The study contributes to scholarship by reframing readiness as not merely psychological but ecologically determined, shaped by school type, power supply stability, and institutional resources.

References

Abodunrin, I., Molade, O., & Awoniyi, R. (2025). An assessment of students' readiness for digital learning in senior secondary schools in Lagos State. *Educational Perspectives*, 13(2), 212–220.

Abubakar, A. M. (2016). *An assessment of the use of ICT in teaching and learning in public secondary schools in Northeastern Nigeria* (Master's thesis, Eastern Mediterranean University (EMU)-Doğu Akdeniz Üniversitesi (DAÜ)). https://hdl.handle.net/11129/2994

Adeoluwa, O. V., Aboderin, O. S., & Omodara, O. D. (2013). The challenges toward implementation of Information and Communication Technology (ICT) in secondary schools in Ondo State, Nigeria. *International Journal of Innovation and Applied Studies*, *2*(3), 259-264. http://www.issr-journals.org/ijias/

Ahunanya, S., Esege, C., & Okorodudu, E. (2025). E-administration adoption in public and private secondary schools in Eti-Osa LGA of Lagos State, Nigeria. *LWATI: A Journal of Contemporary Research*, 22(2), 2–39.

Anorue, C. E., Chukwuma, F., & Ihuarulam, M. O. (2024). Transforming secondary education through technology for sustainable national development: A study of public schools in Lagos State, Nigeria. *Journal of Research and Education for Development in Africa, 1*(2), 1–18.

Asaolu, O. S., & Fashanu, T. A. (2012). Adoption of ICT and its comparative impact on private and public high schools in Lagos State, Nigeria. *International Journal of Science & Emerging Technologies*, *3*(1), 1-6.

Asuquo, E. N., Bassey, A. E., Onasanya, T. O., & Agbor, R. B. (2023). *Nigerian senior secondary school students' engagement of digital technologies for learning.* Paper presented at the Conference of the Association for Innovative Technology Integration in Education, CPES Hall, Federal University of Technology, Minna, Nigeria.

Creswell, J. W. (2014). *Qualitative, quantitative and mixed methods approaches*. Sage.

David-Olawade, A. C., Wada, O. Z., Adeniji, Y. J., Aderupoko, I. V., & Olawade, D. B. (2025). Artificial intelligence readiness among healthcare students in Nigeria: A cross-sectional study assessing knowledge gaps, exposure, and adoption willingness. *International Journal of Medical Informatics*, 106085. https://doi.org/10.1016/j.ijmedinf.2025.106085

Ejimaji, E. U. & Ellah, A. O. (2014). *Fundamental of educational research methods and statistics for higher institutions.* Network Printing Press. https://wajofel.org/index.php/wajofel/article/view/167

George, D., & Mallery, P. (2020). *IBM SPSS Statistics 26 step by step: A simple guide and reference* (16th ed.). Routledge.

Guobadia, F. E., & Ekuobase, G. O. (2024). An estimation of digital learning culture index of secondary education in Nigeria. *Education Research International*, *2024*(1), 6671155. https://doi.org/10.1155/2024/6671155

Hwang, G. J., & Tu, Y. F. (2024). Roles and research trends of artificial intelligence in secondary education: A review of AI-supported learning environments. *Computers and Education: Artificial Intelligence, 6,* 100204. https://doi.org/10.1016/j.caeai.2024.100204

Ife-Abodunrin, M. O., & Roseline, A. (2025). An assessment of students' readiness for digital learning in senior secondary schools in Lagos State. *Educational Perspectives*, *13*(2), 212-220.

Imiruaye, J. E., & Christogonus-Anyanwu, O. (2024). Principal use of ICT for effective administration of public secondary schools in Rivers State, Nigeria. *International Journal of Economics, Environmental Development and Society*, 5(3), 377-388.

Israel, G. D. (1992). *Determining Sample Size*. Gainesville, FL: University of Florida, IFAS Extension.

Jacob, O. N., & Dahir, N. (2021). Challenges preventing public primary school students from using information communication technology for learning in Nigeria and the way forward. *Electronic Research Journal of Social Sciences and Humanities*, *3*, 45-52.

John, M. O., & Aliyu, U. M. A. R. (2024). Educational infrastructure and its impact on academic performance in Nigerian schools. *Iconic Research and Engineering Journals*, *8*(6), 497-502.

Karami, A. M. A. (2024). An investigative study of students' readiness for digital classroom learning in post-COVID-19 pandemic in Air Force Institute of Technology (AFIT) Kaduna, Nigeria. *Research Review*, *5*(2). Retrieved from http://researchreview.in/index.php/rr/article/view/149

Karan, B., & Angadi, G. R. (2025). Factors influencing readiness for the incorporation of artificial intelligence at school context. *African Journal of Science, Technology, Innovation and Development*, 17(4), 545–564. https://hdl.handle.net/10520/ejc-aa_ajstid_v17_n4_a545

Koo, M., & Yang, S. W. (2025). Likert-Type Scale. *Encyclopedia*, *5*(1), 18. https://doi.org/10.3390/encyclopedia5010018

Malima, P., Machumu, H., & Mtawa, N. (2023). *Digital skills and learning in Tanzania secondary schools: Students and teachers' influence*. **Qeios, 5**(9). https://doi.org/10.32388/QJU9PS.2

Mienye, I. D., Sun, Y., & Ileberi, E. (2024). Artificial intelligence and sustainable development in Africa: A comprehensive review. *Machine Learning with Applications*, 18, 100591. https://doi.org/10.1016/j.mlwa.2024.100591

Mutiso, R. M. (2024). AI in Africa: Basics over buzz. *Science*. https://doi.org/ado8276

Nuezca, A. P., Tangcawan, I. S. L. A., & Dequinan, T. K. (2024, November). Students' Digital Literacy Competence, Attitude, and Readiness Toward Technology-Integrated Learning. In *4th International Conference on Education and Technology (ICETECH 2023)* (pp. 300-309). Atlantis Press.

National Population Commission. (2026). 2006 Nigerian national population census. https://nationalpopulation.gov.ng/

Nwuke, T. J., & Yellowe, A. N. (2025). Managing education in Nigeria and the emerging technologies in the 21st century classroom. *World Journal of Innovation and Modern Technology*, *9*(1), 1-14.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Obed-Chukwuka, A. N. (2025). Revitalizing secondary education for sustainable development and economic growth in Nigeria. *International Journal of Educational Management*, *1*(2), 313–324. https://ijedm.com/index.php/ijedm/article/view/62

Odeajo, O., & Odefadehan, C. (2025). Investigating the Current State of Educational Facilities in Secondary Schools in Lagos, Nigeria. *Journal of Education Research and Library Practice*. https://africanscholarpub.com/ajerlp/article/view/753

Okolo, M. A. (2019). Assessment of the availability and utilization of information communication technology (ICT) resources in public and private secondary schools in Abuja, Nigeria. *International Journal of Scientific and Research Publications*, *9*(2), 8613. https://doi.org/10.29322/IJSRP.9.02.2019.p8613

Onuyi, A. B. (2024). Information and communication technology (ICT): Availability and effects on secondary school students' academic performance in Kogi State, Nigeria. *Nigerian Online Journal of Educational Sciences and Technology*, *6*(1).

Orji, S. C., & Ukeh, E. C. (2022). ICT integration in the development of Nigerian educational system: Challenges and prospects. *Journal of Education and Society*, *12*(1), 2250–2259. https://www.bwjournal.org/index.php/bsjournal/article/view/3940

Rana, M. M., Siddiqee, M. S., Sakib, M. N., & Ahamed, M. R. (2024). Assessing AI adoption in developing country academia: A trust and privacy-augmented UTAUT framework. *Heliyon*, 10(18), e37569. https://doi.org/10.1016/j.heliyon.2024.e37569

Ukaoha, K. C., Nwankwo, W. N., Onoshakpor, R., Acheme, I. D., Ugwunna, C., Ekechukwu, C. P., & Otokiti, K. (2025). The impact of power supply on open and distance e-learning (ODeL) infrastructure in Nigeria: Challenges and sustainable solutions. *Journal of Modern Science and Technology*, *1*(1), 119–132.

Umennuihe, C. L., Shu'ara, J., Okechukwu, F. O., Alutu, C. E., & Umennuihe, A. E. (2023). Availability and the extent of utilization of information communication technology among senior secondary school students in Nsukka local government area, Enugu State. *Journal for Family & Society Research*, *2*(1). https://doi.org/10.66043/jfsr.v2i1.42

Varzaru, A. A., & Ghiță, C. R. (2025). Assessing digital technologies' adoption in Romanian secondary schools. *Applied Sciences*, *15*(11), 6157. https://doi.org/10.3390/app15116157

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Yamane, T. (1967). *Statistics: An Introductory Analysis* (2nd ed.). New York: Harper and Row.

Zhang, Y., Liu, H., Chen, X., & Wang, L. (2025). Generative artificial intelligence in secondary education: Applications and effects on students' innovation skills and digital literacy. *PLOS ONE*, *20*(5), e0323349. https://doi.org/10.1371/journal.pone.0323349