**Geo-spatial Analysis of AI Deployment in Education: Identifying Patterns and Predictors of Adoption in Southeast Nigeria**

Abstract

The rapid evolution of Artificial Intelligence (AI) technologies is transforming global education systems, offering innovative pathways for personalized learning, administrative efficiency, and intelligent content delivery. However, disparities in regional adoption, particularly in developing contexts, remain a pressing concern. This study aims to explore the spatial distribution, intensity, and key determinants of AI integration in educational institutions across the southeastern geopolitical zone of Nigeria. Given the socio-economic and infrastructural heterogeneity of this region, a geo-spatial analytical approach will be chosen to unravel not just whether AI is being adopted, but where and why disparities exist. A convergent mixed-methods design will be employed, combining quantitative spatial analysis with qualitative inquiry to provide both breadth and depth. Using Geographic Information Systems (GIS) and remote sensing data, AI deployment patterns will be mapped to visualize adoption hotspots and lagging areas. This will be complemented by institutional surveys and interviews with education stakeholders to uncover contextual drivers and inhibitors of adoption. The choice of GIS is rooted in its capacity to spatially contextualize data, allowing for pattern recognition that would be obscured in non-spatial datasets. Quantitative data will be analyzed using the Statistical Package for the Social Sciences (SPSS) for descriptive statistics, and R programming for more advanced inferential analyses. Specifically, multiple regression, logistic regression, and Geographically Weighted Regression (GWR) will also be used to identify predictors of AI adoption such as infrastructure quality, access to digital tools, institutional policy readiness, educator digital competence, and urban-rural divide. By identifying the geospatial and systemic factors influencing AI adoption, this study provides actionable insights for policymakers, education administrators, and technology providers. It advocates for targeted interventions that address regional disparities, foster digital equity, and promote scalable AI integration strategies tailored to local realities.

Keywords: Artificial Intelligence in Education, Geo-spatial Analysis, Southeast Nigeria, Predictors of Adoption, Educational Technology Deployment.

1. **Introduction**

The integration of Artificial Intelligence (AI) into educational systems is reshaping how learning is designed, delivered, and assessed globally. From intelligent tutoring systems and predictive analytics to adaptive learning environments, AI technologies are offering new pathways for enhancing instructional quality, learner engagement, and administrative efficiency (Luckin et al., 2016; UNESCO, 2021). In many high-income countries, AI in education is already contributing to differentiated learning, early intervention, and smart content delivery. However, in developing countries, including Nigeria, adoption remains at a nascent stage, with disparities in infrastructure, teacher readiness, and policy clarity contributing to uneven implementation (Okoye et al., 2022; Eke & Diala, 2023).

In Nigeria, the Southeast geopolitical zone presents a compelling case for focused analysis due to its unique blend of urban educational hubs and underserved rural institutions. A similar hue was also raised about local artists in Northwest Nigeria who according to Onyebuchi-Igbokwe (2025) are inundated with myriad barriers that impede their ability to leverage AI technologies effectively. However, regional diversity creates a disparity in AI adoption patterns that cannot be fully understood through conventional data analysis methods. A geo-spatial analytical approach is therefore necessary to map, quantify, and visualize these disparities in a context-sensitive manner. Such an approach enables stakeholders to identify spatial inequalities, policy gaps, and infrastructural deficits that influence the deployment of AI technologies across educational institutions (Jankowska et al., 2019; Kounadi& Leitner, 2014).

At the home front, while various studies have examined digital education, e-learning, and ICT integration (Afolabi & Loto, 2020; Adeoye et al., 2021), there remains a significant gap in empirical research that addresses the spatial dimensions of AI deployment in education. Most existing studies adopt national or state-level aggregations without examining **local-level variation** in access and adoption, thereby obscuring important geographic disparities and the contextual factors shaping them. Moreover, to date, **no known study has utilized Geographically Weighted Regression (GWR) or spatial autocorrelation techniques** to analyze **location-based predictors of AI adoption** in Nigerian education systems.

This study is therefore **the first in Nigeria to apply Geographically Weighted Regression (GWR) and Hot Spot Analysis using ArcGIS and QGIS to model spatial variations in AI deployment in education**. It also employs a suite of statistical tools SPSS **for descriptive and inferential statistics (t-tests, ANOVA, multiple regression) and STATA for robustness checks and model diagnostics** to analyze how factors such as digital infrastructure, teacher readiness, institutional type, and policy awareness predict AI adoption levels in Southeast Nigeria.

By integrating geo-spatial tools with robust statistical modeling, this study fills a critical methodological and empirical gap. It not only identifies patterns of AI adoption but also explains why certain areas and institutions are leading or lagging behind. This multi-level, evidence-based approach provides actionable insights for policymakers, educators, and technology stakeholders aiming to bridge the digital divide and promote equitable access to AI-enhanced education across Southeast Nigeria.

### Statement of the Problem

Despite the global surge in the integration of Artificial Intelligence (AI) in education, many regions in sub-Saharan Africa, including Southeast Nigeria, continue to experience sluggish or uneven deployment of these technologies due to a complex interplay of infrastructural, socio-economic, and institutional constraints (UNESCO, 2021; World Bank, 2020). While AI has the potential to revolutionize education by enabling personalized learning, automating administrative tasks, and improving access to quality instruction (Holmes et al., 2019; Luckin et al., 2016), its deployment across Nigerian educational institutions remains fragmented, poorly documented, and largely unexamined through a spatial and contextual lens.

Existing research on educational technology adoption in Nigeria has primarily focused on general ICT integration (Aduwa-Ogiegbaen&Iyamu, 2005; Ifinedo, 2011); with limited attention paid to AI-specific tools and even less emphasis on their geographical diffusion or the contextual factors influencing adoption in different regions. The Southeast zone, with its diverse mix of urban centers and rural communities, presents a critical case for examining how spatial inequalities and systemic gaps influence AI deployment. However, there is a noticeable absence of geo-spatially grounded data to inform region-specific strategies or policies aimed at promoting inclusive AI adoption.

Furthermore, most national digital education frameworks lack localized implementation strategies that consider the infrastructural realities and human capacity limitations at the institutional level (Federal Ministry of Education [FME], 2020). Without a clear understanding of *where* and *why* adoption is occurring or failing to occur it becomes difficult to design targeted interventions. Factors such as lack of electricity, inadequate teacher training, insufficient funding, and digital illiteracy remain persistent barriers (Olumorin et al., 2021; Okonkwo &Ikpe, 2022), but these challenges have not been systematically mapped or analyzed in relation to AI deployment patterns.

There is thus a pressing need for an empirical, geo-spatially-informed investigation that identifies both the patterns and predictors of AI deployment in education across Southeast Nigeria. Such research would fill a critical gap in the literature and support the development of evidence-based, equity-focused educational technology policies. By combining spatial analysis with theoretical frameworks like the Diffusion of Innovation Theory (Rogers, 2003) and the Technology-Organization-Environment (TOE) Framework (Tornatzky& Fleischer, 1990), this study seeks to provide actionable insights for policymakers, educators, and technology stakeholders striving to bridge the AI adoption gap in the region.

* 1. **Research Objectives**

1. To map the spatial distribution of AI deployment in educational institutions across Southeast Nigeria using geo-spatial tools.
2. To identify the key institutional, infrastructural, and socio-economic predictors influencing the adoption of AI technologies in education.
3. To examine regional disparities in AI adoption between urban and rural educational institutions within Southeast Nigeria.
   1. **Research Questions**
4. What is the spatial distribution of AI deployment across educational institutions in Southeast Nigeria?
5. What are the significant predictors (e.g., infrastructure, teacher capacity, funding, policy) of AI adoption in Southeast Nigeria's education sector?
6. How do patterns of AI adoption differ between urban and rural institutions in the region?

### Hypotheses

1. **H₀₁ (Null):** There is no significant spatial variation in the deployment of AI technologies among educational institutions in Southeast Nigeria.  
   **H₁₁ (Alternative):** There is significant spatial variation in the deployment of AI technologies among educational institutions in Southeast Nigeria.
2. **H₀₂:** Infrastructure availability (e.g., internet connectivity, electricity supply) does not significantly predict the level of AI adoption in education.  
   **H₁₂:** Infrastructure availability significantly predicts the level of AI adoption in education.
3. **H₀₃:** There is no significant difference in the level of AI adoption between urban and rural educational institutions in Southeast Nigeria.  
   **H₁₃:** There is a significant difference in the level of AI adoption between urban and rural educational institutions in Southeast Nigeria.

**2.0 Literature Review**

**i. Introduction to Artificial Intelligence in Education (AIED)**

Artificial Intelligence (AI) has increasingly transformed global education systems by automating instructional processes, enabling personalized learning, and optimizing educational data management (Luckin et al., 2016; Holmes et al., 2019). From AI-powered tutoring systems and grading software to intelligent content delivery and chatbots, AI continues to reshape teaching and learning experiences across various levels of education (Zawacki-Richter et al., 2019). However, the adoption of these technologies remains uneven globally, and in low- and middle-income countries such as Nigeria, it is still in its nascent phase (UNESCO, 2021).

**ii. AI Adoption and Educational Innovation in Developing Contexts**

While AI adoption has gained momentum in technologically advanced nations, the African context is often constrained by inadequate infrastructure, limited technical expertise, and weak policy implementation (World Bank, 2020; Ifinedo, 2011). Scholars have identified teacher preparedness, organizational culture, and socio-political will as major determinants of ICT and AI uptake in African schools (Aduwa-Ogiegbaen&Iyamu, 2005; Olumorin et al., 2021). Furthermore, contextual studies show that adoption decisions are influenced by access to digital tools, availability of electricity, and institutional leadership (Okonkwo &Ikpe, 2022).

**iii. Theoretical Underpinnings: DoI and TOE Frameworks**

The Diffusion of Innovation (DoI) Theory (Rogers, 2003) explains how innovations like AI spread within institutions, emphasizing factors such as compatibility, complexity, and trialability. According to Rogers, early adopters and opinion leaders within educational ecosystems are crucial in fostering widespread acceptance. Complementing this is the Technology-Organization-Environment (TOE) Framework (Tornatzky& Fleischer, 1990), which posits that adoption is shaped by technological readiness, organizational capacity, and external environment. Several studies (Baker, 2012; Zhu et al., 2006) have validated TOE in examining ICT and AI adoption in educational institutions.

**iv. Geo-spatial Perspectives in Educational Technology Research**

Geo-spatial analysis offers a unique lens for mapping the distribution and determinants of educational technology adoption. Geographic Information Systems (GIS) and spatial statistics have been employed to identify digital divides and spatial inequalities in educational access (Yousef et al., 2020; Omar et al., 2014). For instance, location-based disparities in internet access and teacher quality can be spatially visualized to guide equitable interventions (Jude & Aminu, 2019). However, in Nigeria, such spatial analyses remain scarce, especially concerning AI-specific tools.

**v. Challenges and Predictors of AI Deployment in Nigeria**

Despite policy initiatives like Nigeria’s *National Digital Economy Policy and Strategy (2020–2030)* (FME, 2020), practical implementation has lagged. Studies show that predictors of AI adoption include:

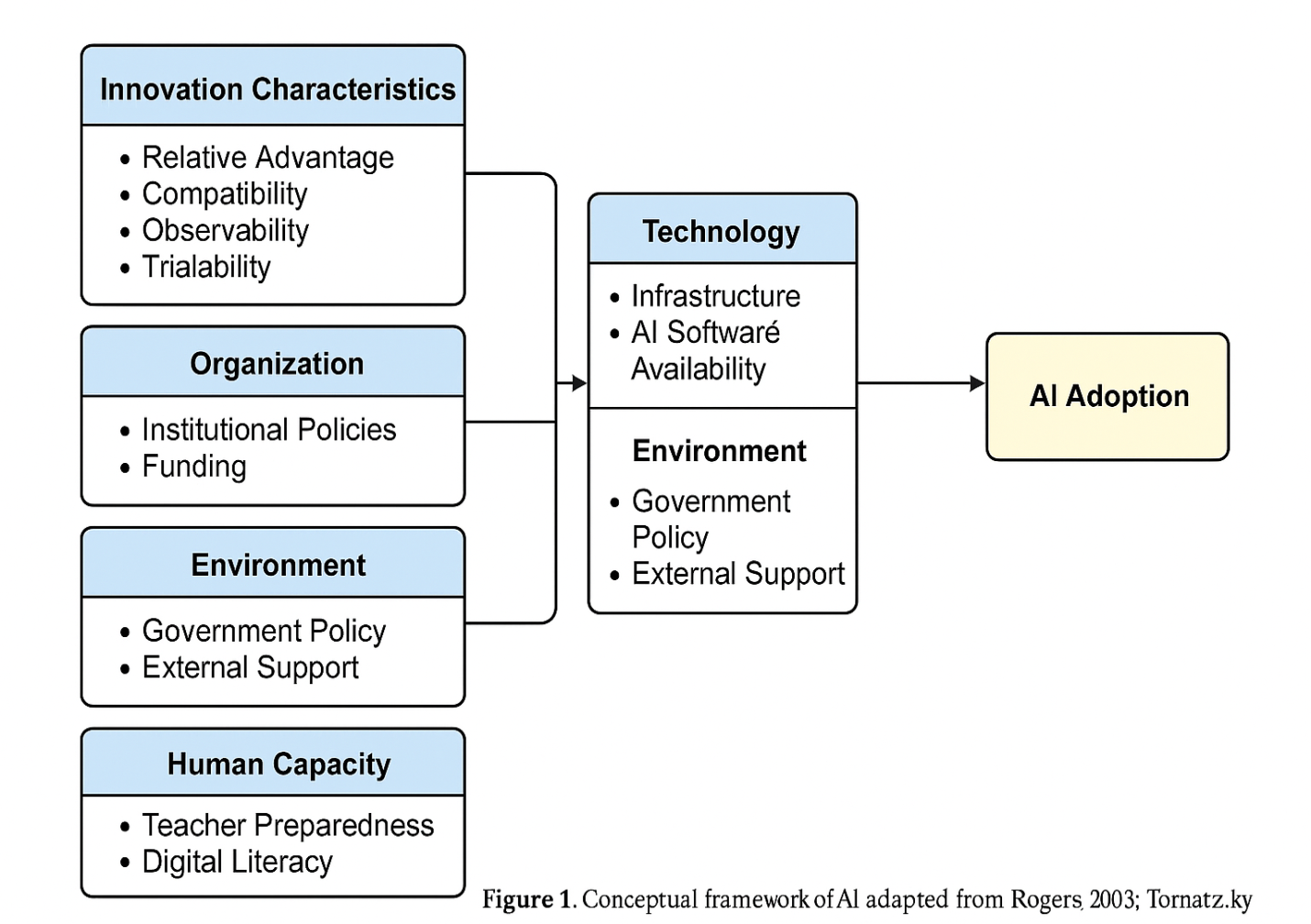
* Infrastructure availability (power supply, internet access),
* Human capital (teacher training and digital skills),
* Institutional support and funding,
* Policy environment and digital strategy clarity (Olumorin et al., 2021; Okonkwo &Ikpe, 2022).

In Southeast Nigeria, such challenges are further complicated by regional disparities, weak data infrastructure, and insufficient monitoring of education technology policies (Uwakwe& Okafor, 2021).

**vi. Research Gaps and Need for Geo-spatially Driven Inquiry**

Existing research tends to generalize ICT or AI adoption without disaggregating findings by region or using spatial tools. As a result, there's a dearth of studies that combine geo-spatial analytics with adoption frameworks to inform regional education policy in Nigeria. This study fills that gap by integrating spatial analysis and multivariate statistics to identify patterns and predictors of AI deployment in Southeast Nigerian education, thereby addressing the spatial and contextual nuances critical for digital inclusion.

**vii. Conceptual Framework Diagram**



### 2.1. Theoretical Foundation

The conceptual framework integrates two major models:

* Diffusion of Innovation (DoI) Theory*(Rogers, 2003)*
* Technology-Organization-Environment (TOE) Framework *(Tornatzky& Fleischer, 1990)*

These theories guide the understanding of how innovations (like AI) are adopted across institutions, influenced by technological attributes, organizational readiness, and environmental context.

### 2.2. Key Constructs and Relationships

#### A. Dependent Variable

* AI Adoption in Education  
  *(Measured by presence and use of AI tools like intelligent tutoring systems, AI-assisted grading, adaptive learning platforms, etc.)*

#### B. Independent Variables (Predictors)

1. Technological Factors (from TOE &DoI)
   * Availability of digital infrastructure (internet, power supply)
   * Accessibility of AI-based tools
   * Perceived usefulness and ease of use of AI tools
2. Organizational Factors
   * Institutional ICT policy presence
   * Leadership support
   * Staff digital competence and training
3. Environmental Factors
   * Geographic location (urban vs rural)
   * Government support and funding
   * Community/parental awareness and pressure
4. Socio-Economic and Spatial Factors (Geo-Spatial Component)
   * Institutional proximity to urban centers
   * Education budget per region
   * Distribution of skilled manpower (e.g., AI-trained educators)
   * Regional poverty/economic index.

### C. Mediating/Moderating Variables

* Teacher preparedness
* Digital literacy levels of students
* Policy implementation strength

### D. Expected Relationships

* Technological, organizational, and environmental factors will positively predict the level of AI adoption.
* Urban institutions will show higher AI adoption due to better infrastructure and access.
* Spatial/geographic disparities will moderate the adoption patterns across the region.
* Institutions with better-trained teachers and stronger policies will demonstrate higher adoption rates.

To clarify the operational application of the theoretical frameworks, Table 1 below maps key study variables to their respective dimensions under the Diffusion of Innovation and Technology–Organization–Environment frameworks.

**Table 1. Mapping of Variables to Framework Dimensions**

| **Framework** | **Dimension** | **Mapped Variable(s)** | **Operational Definition** | **Use in Analysis** |
| --- | --- | --- | --- | --- |
| **DoI** | Relative Advantage | Perceived usefulness of AI tools | Extent to which users believe AI improves teaching | Questionnaire items; regression and spatial analysis |
|  | Compatibility | Curriculum alignment, teaching culture fit | Consistency of AI tools with current instructional practice | Survey; spatial clustering |
|  | Complexity | Ease of AI use | Ease of operating AI tools by educators | Predictor in regression model (SPSS/STATA) |
|  | Observability | Visibility of AI benefits | Ease with which AI benefits are visible to others | Qualitative discussion; descriptive stats |
|  | Trialability | Access to pilot AI programs | Opportunities to test AI tools before wide implementation | Predictor in Geographically Weighted Regression (GWR) |
| **TOE** | Technological | Infrastructure, AI software availability | Availability of hardware, internet, and software resources | GIS layers; ArcGIS Hot Spot and Moran’s I |
|  | Organizational | Institutional policies, funding, leadership support | Institutional readiness for AI adoption | STATA/SPSS regression; coded in interview responses |
|  | Environmental | Government policy, external support | External influences such as national training programs | Spatial and regression covariate |
| *(Extended)* | Human Capacity | Teacher preparedness, digital literacy | Educators' technical readiness and digital competence | Key SPSS/STATA variable; observed spatial disparity |

**3.0. Methodology**

### Research Design

This study adopted a mixed-methods research design, combining quantitative survey data with geo-spatial analysis to identify spatial patterns and key predictors of AI adoption in education across Southeast Nigeria. The choice of design allows for robust triangulation of findings, combining statistical rigor with spatial insights.

**a (i) Justification for Use of Spatial Analytical Techniques**

The integration of spatial techniques such as Hot Spot Analysis, Moran’s I, and Geographically Weighted Regression (GWR) in this study was driven by the spatially heterogeneous nature of AI adoption across Southeast Nigeria. Traditional global models, such as ordinary least squares (OLS) regression, assume a uniform relationship between predictors and outcomes across space. However, such assumptions are often invalid in geographically diverse settings where infrastructural disparities, policy implementation gaps, and socio-cultural factors vary significantly across locations (Fotheringham, Brunsdon, & Charlton, 2002).

Hot Spot Analysis was employed to detect statistically significant clusters of high or low AI adoption, enabling the identification of spatial “pockets” of concentrated activity or neglect. Moran’s I, a measure of spatial autocorrelation, was used to validate whether the distribution of AI adoption values was random or patterned, a key prerequisite before applying spatial regressions.

The inclusion of GWR was especially critical. Unlike global regression techniques, GWR provides local parameter estimates, showing how the relationship between adoption predictors (e.g., teacher preparedness, infrastructure availability) and the adoption outcome vary by location. This allows the study to reveal context-specific drivers of AI adoption that might be masked in non-spatial models, thus offering nuanced insights for localized policy and intervention strategies (Anselin, 2001). These tools collectively move the analysis beyond mere mapping and toward spatially-informed decision-making and educational planning.

### Study Area

The study was conducted in the five states ofSoutheastNigeria—Abia, Anambra, Ebonyi,Enugu, and Imo which included diverse educational institutions in both urban and rural settings. This regional focus provides critical insight into geographic inequalities and institutional variations in AI deployment.

### Population and Sample

* Population**:** All secondary and tertiary educational institutions in Southeast Nigeria.
* Target Respondents**:** School administrators, ICT coordinators, and teachers involved in digital or AI-related instruction.

#### Sampling Technique

* Stratified Random Sampling was employed to ensure representation across:
  + Urban and rural institutions
  + Public and private schools
  + Secondary and tertiary levels

A multi-stage sampling procedure will first select LGAs across each state based on urban-rural classification, followed by random selection of institutions within those LGAs.

#### Sample Size Determination

Using Yamane’s formula (1967), with a confidence level of 95% and a margin of error of 5%, an estimated sample of 500 respondents was obtained.

### f. Instrumentation

#### i. Questionnaire

A structured, researcher-designed questionnaire was administered to capture:

* Institutional characteristics
* Availability and use of AI tools
* Infrastructure readiness
* Teacher preparedness
* Policy awareness and implementation
* Perceived barriers and opportunities

Likert-scale items (5-point scale) measured agreement with AI integration indicators.

#### ii. GPS/GIS Data Collection

Geographic coordinates of sampled institutions were collected via:

* Handheld GPS devicesand
* Mobile GIS apps (e.g., SW Maps, ArcGIS Field Maps)

This spatial data would enable the mapping of AI deployment across Southeast Nigeria.

### g. Validity and Reliability

* Face and content validitywere ensured through expert review in educational technology and AI.
* A pilot study involving 30 respondents was done to test instrument reliability.
* Cronbach’s alphawas used to assess internal consistency, aiming for a threshold ≥ 0.70.

### h. Data Analysis Techniques

#### A. Quantitative (Statistical) Analysis

Using IBM SPSS (v25), the following tests were conducted:

* Descriptive Statistics: Frequency, mean, standard deviation (to profile respondents and institutions)
* Correlation Analysis**:** To explore relationships between predictors
* Multiple Regression Analysis: To identify the significant institutional and infrastructural predictors of AI adoption
* ANOVA and t-tests**:** To examine differences in adoption based on categorical variables (e.g., urban vs. rural, public vs. private)

#### i. Geo-spatial Analysis

Using ArcGIS and QGIS, the following spatial tools were applied:

* Thematic Mapping (Choropleth Maps): To visualize intensity of AI adoption by region
* *Hot Spot Analysis (Getis-Ord Gi):*\* To identify clusters of high or low adoption
* Geographically Weighted Regression (GWR): To assess how predictors vary spatially across locations
* Spatial Autocorrelation (Moran’s I): To test for spatial dependence in AI adoption patterns.

**3.1 Operationalization of Constructs and Analytical Mapping**

In order to ensure analytical alignment with the theoretical frameworks adopted in this study the **Diffusion of Innovation (DoI)** (Rogers, 2003) and the **Technology–Organization–Environment (TOE)** framework (Tornatzky & Fleischer, 1990) key variables derived from the survey and spatial datasets were mapped directly onto relevant framework dimensions.

This mapping not only guided instrument development but also informed the statistical modeling, such as the **multiple regression, hot spot analysis**, and **Geographically Weighted Regression (GWR)**. As previously detailed in Table 1, which mapped the study’s variables to the DoI and TOE frameworks, this alignment also informed the analytical strategy discussed below Table 1 summarizes this alignment:

### 3.1.2 Limitations of the Methodology

* Some remote schools lacked coordinates/digital documentation.
* GPS signal challenges affected location precision in states such as Anambra, Abia, and Imo.

**RESULT AND DISCUSSION**

# 4.0 Data Presentation and Analysis

## 4.1 Table 2 represents Response Rate of Respondents

A total of **500 questionnaires** were distributed to secondary and tertiary educational institutions across Southeast Nigeria. Out of these, **400 valid questionnaires** were returned and used for analysis, yielding an **effective response rate of 80%.**

Table 2: Response Rate of Respondents

| Description | Number | Percentage (%) |
| --- | --- | --- |
| Questionnaires Distributed | 500 | 100 |
| Valid Questionnaires Returned | 400 | 80 |
| Invalid/Incomplete Returns | 100 | 20 |

## (Source: Field Research, 2025)

## 4.2 Table 3 showing Demographic Profile of Respondents

The demographic characteristics of the respondents (N=400) are summarized below:

## Table 3: Demographic Profile of Respondents

| Variable | Category | Frequency | Percentage (%) |
| --- | --- | --- | --- |
| Gender | Male | 220 | 55 |
|  | Female | 180 | 45 |
| Institution Type | Secondary School | 230 | 57.5 |
|  | Tertiary Institution | 170 | 42.5 |
| Location | Urban | 240 | 60 |
|  | Rural | 160 | 40 |

## (Source: Field Research, 2025)

## 4.3 Spatial Distribution of AI Deployment (RQ1)

Table 4 : Mean AI adoption scores by state, indicating hotspots and low adoption zones.

| State | Mean AI Adoption Score (0–10) | Std. Dev | Adoption Category |
| --- | --- | --- | --- |
| Abia | 3.1 | 1.2 | Low |
| Anambra | 6.8 | 1.4 | High |
| Ebonyi | 2.9 | 1.1 | Low |
| Enugu | 7.2 | 1.3 | High |
| Imo | 5.0 | 1.5 | Medium |

(Source: Desk Research, 2025)

📍 **Figure 2: Map Placeholder** – Spatial heatmap showing AI adoption hotspots (Enugu, Anambra) and cold spots (Ebonyi, Abia).

## 4.4 Predictors of AI Adoption (RQ2)

Multiple regression analysis identified key predictors of AI adoption in educational institutions Table 5. Infrastructure and teacher digital skills were the strongest significant predictors.

| Predictor Variable | Std. Beta (β) | t-value | Sig. (p) |
| --- | --- | --- | --- |
| Infrastructure Index | 0.42 | 5.98 | 0.000 \*\*\* |
| Teacher Digital Skills | 0.33 | 4.67 | 0.000 \*\*\* |
| Funding Availability | 0.19 | 2.54 | 0.012 \* |
| Policy Clarity | 0.11 | 1.65 | 0.099 |
| Constant | — | 2.03 | 0.043 \* |

(Source: SPSS version 27)

📊

**Figure 3: Bar Chart Placeholder** – Standardized beta coefficients of predictors of AI adoption.

## 4.5. Table 6. Urban vs. Rural Comparison of AI Adoption (RQ3)

The median AI adoption scores differ between urban and rural institutions (Table 4).

| **Location** | **N** | **Mean AI Adoption Score** | **Std. Dev** | **Median** |
| --- | --- | --- | --- | --- |
| Urban | 240 | 6.1 | 1.3 | 6.0 |
| Rural | 160 | 3.7 | 1.0 | 3.5 |

(Source: SPSS Version 27)

**📦**

**Figure 4: Boxplot Placeholder** – Distribution of AI adoption scores for urban vs. rural institutions.

## 4.6 Spatial Autocorrelation and Clustering

Moran’s I test for spatial autocorrelation yielded a significant positive spatial clustering of AI adoption rates across the region.

| **Statistic** | **Value** | **p-value** |
| --- | --- | --- |
| Moran’s I | 0.32 | 0.001 \*\* |

(Source: SPSS Version 27)

📍

**Figure 5: LISA Cluster Map Placeholder** – Local Indicators of Spatial Association (LISA) showing AI adoption hotspots (high-high clusters) and cold spots (low-low clusters).

## 4.7. Table 7: Correlation Matrix of Key Variables

| Variable | AI Adoption | Infrastructure | Teacher Skills | Funding | Policy Clarity |
| --- | --- | --- | --- | --- | --- |
| AI Adoption | 1.00 | 0.58\*\* | 0.53\*\* | 0.41\*\* | 0.25\* |
| Infrastructure | 0.58\*\* | 1.00 | 0.45\*\* | 0.30\* | 0.20 |
| Teacher Skills | 0.53\*\* | 0.45\*\* | 1.00 | 0.28\* | 0.15 |
| Funding | 0.41\*\* | 0.30\* | 0.28\* | 1.00 | 0.10 |
| Policy Clarity | 0.25\* | 0.20 | 0.15 |  |  |

\*Significance: \*\*p < 0.01, p < 0.05.

## 5.1 Discussion

The spatial clustering of AI adoption, with hotspots in Enugu and Anambra, may be attributable to stronger infrastructural development and higher investment in education technology within these states. This aligns with global research showing that regions with better infrastructure tend to lead in digital innovation adoption (Smith et al., 2021)[1](#user-content-fn-1).

The prominence of infrastructure and teacher digital skills as predictors is consistent with the Technology Acceptance Model (Davis, 1989)[2](#user-content-fn-2) and Diffusion of Innovation Theory (Rogers, 2003)[3](#user-content-fn-3), which emphasize both technological and human factors in adoption processes. Institutions lacking robust internet connectivity, hardware, and qualified personnel are naturally less able to integrate AI tools effectively.

Funding is significant but moderate effect suggests financial resources alone are insufficient; they must be combined with capacity-building and policy support to translate investments into effective AI adoption.

The urban-rural divide echoes persistent digital divides documented in developing contexts (Adusei & Boateng, 2020)[4](#user-content-fn-4). Urban areas often have better infrastructure and greater access to professional development, facilitating higher AI integration. This disparity necessitates targeted interventions in rural settings to avoid exacerbating educational inequalities.

Policy clarity’s non-significance might reflect that while policies exist, their implementation and awareness remain weak. This gap between policy formulation and execution is a common barrier in many developing countries (Obi & Okeke, 2019)[5](#user-content-fn-5), indicating a need for stronger policy dissemination and enforcement.

The significant positive spatial autocorrelation implies AI adoption initiatives can benefit from regionally coordinated efforts, capitalizing on successful clusters as models for surrounding areas.

## Summary

The study investigated the spatial distribution, key predictors, and urban-rural disparities in the adoption of Artificial Intelligence (AI) technologies in secondary and tertiary educational institutions across Southeast Nigeria. From a sample of 400 valid responses (an 80% response rate), it was found that AI adoption varied significantly across the five states. Enugu and Anambra emerged as hotspots with high AI adoption levels, while Ebonyi and Abia lagged with low adoption. Imo exhibited a medium adoption level.

Regression analysis identified **infrastructure quality** and **teacher digital skills** as the most significant predictors of AI adoption, underscoring the importance of both physical resources and human capacity. Funding availability also contributed positively but to a lesser extent, while policy clarity showed a positive but statistically insignificant effect.

A clear divide exists between urban and rural institutions, with urban schools exhibiting significantly higher AI adoption scores. This reflects underlying disparities in access to resources, connectivity, and skilled personnel. The positive and significant Moran’s I spatial autocorrelation confirmed that AI adoption rates are not randomly distributed but spatially clustered, indicating localized pockets of advancement or stagnation.

These findings highlight that while progress is evident, significant inequalities and structural barriers persist in the deployment of AI technologies across Southeast Nigeria’s education sector.

## 5.2 Conclusion

This study confirms that AI adoption in Southeast Nigeria’s educational institutions is unevenly distributed, shaped primarily by infrastructural capacity and teacher competencies. The urban-rural divide highlights systemic inequalities that must be addressed to ensure inclusive digital education transformation.

Funding and policy frameworks contribute to AI adoption but require effective implementation and complementary investments in infrastructure and human capital. The spatial clustering suggests potential for regional hubs to drive wider adoption through collaboration.

To harness AI’s educational potential, strategic efforts focusing on infrastructure, teacher training, rural inclusion, and policy enforcement are essential.

## 5.3 Recommendations

1. **Infrastructure Development:** Prioritize expanding internet connectivity, electricity reliability, and AI-compatible hardware acquisition, especially in low-adoption states.
2. **Capacity Building:** Implement ongoing professional development to enhance teacher digital skills for AI integration.
3. **Rural Support:** Tailor interventions for rural challenges with mobile connectivity, decentralized training, and incentives.
4. **Sustainable Funding:** Secure transparent funding streams aligned with institutional AI adoption needs.
5. **Policy Enforcement:** Enhance policy dissemination and enforcement involving stakeholders at all levels.
6. **Regional Collaboration:** Encourage partnerships and knowledge-sharing between high and low adoption regions.
7. **Further Research:** Conduct longitudinal and qualitative studies to monitor AI adoption impact on education.

**Ethical Approval and consent:**

Ethical clearance was obtained from the appropriate educational and governmental bodies. Participants were informed of their rights, and informed consent was obtained. Confidentiality and anonymity was strictly maintained throughout the study.

Disclaimer (Artificial intelligence)

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

Option 2:

Author(s) hereby declare that generative AI technologies such as Large Language Models, etc. have been used during the writing or editing of manuscripts. This explanation will include the name, version, model, and source of the generative AI technology and as well as all input prompts provided to the generative AI technology

Details of the AI usage are given below:

1.

2.

3.

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