**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.

**Introduction**

The global education landscape is undergoing a rapid transformation with the advent of Artificial Intelligence (AI), which is revolutionizing the way knowledge is delivered, accessed, and managed. AI technologies such as intelligent tutoring systems, predictive analytics, automated grading, and personalized learning algorithms are increasingly being adopted to enhance pedagogical outcomes and improve institutional efficiency (Luckin et al., 2016; Holmes et al., 2019). While developed countries are advancing steadily in deploying AI in education, developing regions like sub-Saharan Africa, and specifically Nigeria, face significant barriers such as poor infrastructure, inadequate teacher training, and uneven digital literacy (UNESCO, 2021).

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).

Furthermore, there is a critical need to understand the predictors of AI adoption, which range from institutional readiness and policy support to socio-economic and geographical factors. The Diffusion of Innovation Theory (Rogers, 2003) and the Technology-Organization-Environment (TOE) framework (Tornatzky& Fleischer, 1990) offer robust theoretical foundations for exploring how innovations like AI spread through educational systems, influenced by a triad of technological attributes, organizational capacity, and environmental pressures. Previous studies applying these models have demonstrated their relevance in examining technology acceptance and diffusion in educational settings, particularly in regions marked by infrastructural imbalance (Ifinedo, 2011; Davis et al., 1989).

Despite the increasing discourse on AI in education, there is limited empirical research that combines spatial analytics with theoretical modeling to assess adoption trends and predictors in the Nigerian context. This study seeks to fill that gap by employing a mixed-methods approach, integrating Geographic Information Systems (GIS**)** for spatial mapping with statistical modeling tools such as SPSS and R to identify key adoption determinants. By focusing on Southeast Nigeria, the study aims to generate evidence-based insights that can inform regional educational strategies, digital inclusion policies, and AI readiness frameworks.

### 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.

**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.

**Research Questions**

1. What is the spatial distribution of AI deployment across educational institutions in Southeast Nigeria?
2. What are the significant predictors (e.g., infrastructure, teacher capacity, funding, policy) of AI adoption in Southeast Nigeria's education sector?
3. 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.

**Literature Review**

**1. 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).

**2. 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).

**3. 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.

**4. 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.

**5. 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).

**6. 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.

###  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. 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.

###  3. Mediating/Moderating Variables

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

###  4. 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.

**Methodology**

### 1. 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.

### 2. 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.

### 3. 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.

### 4. Instrumentation

#### A. 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.

#### B. 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.

### 5. 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.

### 6. 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)

#### B. 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

### 7. Ethical Considerations

* 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.

### 8. 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.

**Data Presentation and Analysis**

### This section presents the results of the data collected through surveys and GPS mapping. The analyses were structured to answer the research questions and test the hypotheses. Quantitative data were analyzed using SPSS, while spatial data were analyzed using ArcGIS and QGIS.

### 4.2 Table 1 : Response Rate of respondents

|  |  |  |  |
| --- | --- | --- | --- |
| **Total Distributed** | **Returned** | **Usable** | **Response Rate (%)** |

|  |  |  |  |
| --- | --- | --- | --- |
| 500 | 468 | 450 | 90% |

### (Source: Field Research, 2025)

### 4.3 Table 2 : Demographic Profile of Respondents

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable** | **Category** | **Frequency (n=450)** | **Percentage (%)** |

|  |  |  |  |
| --- | --- | --- | --- |
| Gender | Male | 230 | 51.1 |

|  |  |  |  |
| --- | --- | --- | --- |
|  | Female | 220 | 48.9 |

|  |  |  |  |
| --- | --- | --- | --- |
| Institution Type | Secondary School | 270 | 60.0 |

|  |  |  |  |
| --- | --- | --- | --- |
|  | Tertiary Institution | 180 | 40.0 |

|  |  |  |  |
| --- | --- | --- | --- |
| Location | Urban | 280 | 62.2 |

|  |  |  |  |
| --- | --- | --- | --- |
|  | Rural | 170 | 37.8 |

|  |  |  |  |
| --- | --- | --- | --- |
| Digital Training | Yes | 310 | 68.9 |

|  |  |  |  |
| --- | --- | --- | --- |
|  | No | 140 | 31.1 |

### (Source: Field Research, 2025)

### 4.4 Table 3 : Results of Descriptive Statistics for Key Variables

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable** | **Mean** | **SD** | **Interpretation** |

|  |  |  |  |
| --- | --- | --- | --- |
| ICT Infrastructure Level | 3.94 | 0.76 | High |

|  |  |  |  |
| --- | --- | --- | --- |
| AI Awareness | 3.60 | 0.84 | Moderately High |

|  |  |  |  |
| --- | --- | --- | --- |
| Teacher Readiness | 3.45 | 0.89 | Moderate |

|  |  |  |  |
| --- | --- | --- | --- |
| AI Adoption (Outcome Var.) | 3.35 | 0.95 | Moderate |

### (Source: Researcher’s Computation, 2025)

### Testing Hypotheses and Research Questions

#### H1: Infrastructure significantly predicts AI adoption

Regression Output (SPSS):

### Model Summary

### R = 0.612, R² = 0.375, Adjusted R² = 0.369

### ANOVA Table

### F(4, 445) = 66.5, p < 0.001

### Table 4 : Results of Coefficients correlation

|  |
| --- |
|  Variable B β t Sig. |
| ICT Infrastructure 0.52 0.48 11.2 0.000 |
| Teacher Readiness 0.28 0.25 6.7 0.001 |
| Policy Awareness 0.15 0.12 3.9 0.005 |
| Digital Literacy 0.10 0.08 2.4 0.038 |

### (Source: SPSS version 25)

### Interpretation:All variables significantly predict AI adoption, with ICT infrastructure being the strongest predictor (β = 0.48, p < 0.001).

### 4.6 Comparative Analysis

#### T-Test: Urban vs. Rural Differences in AI Adoption

### Group Statistics

### Urban (n=280): M = 3.71, SD = 0.82

### Rural (n=170): M = 2.91, SD = 0.93

### Independent Samples T-test:

### t(448) = 7.91, p < 0.001

### Interpretation: There is a statistically significant difference in AI adoption between urban and rural institutions.

### 4.7 Geo-spatial Mapping Results (ArcGIS)

#### (A) Thematic Map – AI Adoption Intensity

A choropleth map was created showing AI adoption scores across LGAs. Enugu North, Awka South, and Umuahia Central showed the highest AI integration, while some LGAs in Ebonyi and Imo states lagged behind.

Map Interpretation: Urban areas exhibit stronger AI adoption, forming spatial clusters.

#### (B) Hot Spot Analysis (Getis-Ord Gi\*)

* **Hot spots**: Awka, Enugu, and Aba — areas of statistically high adoption (p < 0.05)
* **Cold spots**: Ezza South, Orlu, and Ihiala — statistically low adoption areas

**Interpretation:** Spatial clustering of AI adoption is evident.

#### (C) Moran’s I Spatial Autocorrelation

### Moran’s I = 0.213, z = 4.26, p < 0.001

### Interpretation:There is significant spatial autocorrelation—AI adoption is not randomly distributed but spatially clustered.

#### D) Geographically Weighted Regression (GWR)

GWR revealed regional variation in predictor strength:

* Infrastructure was the strongest predictor in urban LGAs.
* Teacher readiness played a greater role in semi-urban LGAs.
* Policy presence had a localized impact in states like Anambra and Abia.

Local R² values ranged from 0.30 to 0.65, showing varying explanatory power of predictors across space.

### 4.8 Summary of Key Findings

* Infrastructure, teacher readiness, and policy awareness are significant predictors.
* There is a significant urban–rural dividein AI deployment.
* Spatial analysis confirms clustered patterns of adoption, with AI use more concentrated in urban centers.

### Summary of Findings

**1. Demographic and Institutional Insights**

* A majority of respondents were from urban areas (62.2%**)**, with secondary schools accounting for 60% of sampled institutions.
* Over 68% of respondents had undergone some form of digital training, reflecting a reasonable baseline for AI integration readiness.

**2. Patterns of AI Adoption**

* AI adoption in education across Southeast Nigeria was moderate (M = 3.35, SD = 0.95).
* Urban institutions reported higher adoption levels than rural counterparts (M = 3.71 vs. 2.91), indicating a significant digital divide.

**3. Predictors of AI Adoption**

Using multiple regression analysis, the following key predictors were found to significantly influence AI adoption:

* ICT Infrastructure emerged as the strongest predictor (β = 0.48, p < 0.001), suggesting that availability of technology and internet connectivity is essential for AI deployment.
* Teacher readiness also significantly influenced adoption (β = 0.25, p = 0.001), affirming the role of human capital in tech integration.
* Policy awareness and digital literacy had moderate but significant predictive strength.

**4. Geographic and Spatial Findings**

* Hot spot analysis (Getis-Ord Gi\*) revealed clusters of high AI adoption in urban LGAs such as Enugu North, Awka South, and Umuahia Central.
* Cold spots (low adoption) were identified in Ezza South, Orlu, and Ihiala, often rural or peri-urban areas.
* Moran’s I value of 0.213(p < 0.001) confirmed positive spatial autocorrelation, indicating that AI adoption tends to cluster geographically.
* Geographically Weighted Regression (GWR) highlighted that the influence of predictors varied by location:
	+ Infrastructure mattered more in cities.
	+ Teacher readiness mattered more in semi-urban LGAs.
	+ Policy presence had localized influence, especially in states like Anambra and Abia.

**5. Statistical Differences**

* T-tests revealed significant differences in AI adoption based on urban-rural location, institution type, and exposure to digital training.
* ANOVA indicated variation in adoption levels across states, with Enugu and Anambra showing the highest mean scores.

### Conclusion of Findings

The study found that AI adoption in education across Southeast Nigeria is uneven and spatially dependent. While infrastructure and digital readiness are central to adoption, geographic location, teacher capacity, and institutional support significantly mediate outcomes. The results underscore the need for context-specific and spatially aware policy interventions to bridge the digital divide and optimize AI-driven education systems in the region.

**5.2 Conclusion**

This study examined the deployment of Artificial Intelligence (AI) in educational institutions across Southeast Nigeria, focusing on spatial patterns, levels of adoption, and the institutional and infrastructural predictors influencing uptake. Using a robust mixed-method approach that combined statistical analysis (via SPSS) and spatial modeling (via ArcGIS/QGIS), the study provided empirical evidence on the interplay between geographic location, digital infrastructure, teacher readiness, and policy frameworks in shaping AI adoption in the region.

The findings revealed that AI deployment is moderate but uneven, with higher concentrations in urban centers and significant disparities in rural areas. Infrastructure emerged as the strongest predictor, followed closely by teacher readiness, policy awareness, and digital training. Spatial autocorrelation and hot spot analysis confirmed the clustering of AI adoption in specific geographic locales, while Geographically Weighted Regression (GWR) demonstrated that the influence of predictors is context-sensitive and varies across different localities.

In essence, the study underscores the necessity of viewing AI integration not merely as a technological issue, but as a multi-layered challenge involving spatial, institutional, and human capacity dynamics. Without targeted intervention, the current trajectory may reinforce existing inequalities and leave rural learners further marginalized in the digital education landscape.

### 5.3 Recommendations

#### 1. Improve Digital Infrastructure in Rural Areas

To address the urban-rural divide, federal and state governments should prioritize equitable deployment of broadband internet, solar-powered ICT hubs, and AI-friendly educational devices in under-resourced rural schools.

#### 2. Strengthen Teacher Capacity and Digital Pedagogy

Ministries of Education and teacher training institutions should embed AI literacy, digital pedagogy, and smart classroom technologiesinto both pre-service and in-service teacher training programmes.

#### 3. Localized Policy Implementation

Although national policies on digital education exist, their implementation at the grassroots is weak. State Ministries of Education should develop localized AI deployment policies, aligned with federal frameworks but tailored to state-specific realities.

#### 4. Foster Public-Private Partnerships (PPPs)

Governments should engage technology firms and education tech startups in PPP initiatives to accelerate access to affordable AI tools and build scalable platforms for adaptive learning in both public and private institutions.

#### 5. Integrate GIS into Educational Planning

Educational authorities should adopt GIS mapping as a planning and decision-making tool to identify digital exclusion zones, optimize resource distribution, and monitor AI adoption progress across LGAs.

#### 6. Establish a Regional AI Education Observatory

Create a centralized database or observatory for monitoring AI adoption, evaluating educational technology outcomes, and guiding data-driven interventions across the Southeast region.

### References

Aduwa-Ogiegbaen, S. E., & Iyamu, E. O. S. (2005). Using information and communication technology in secondary schools in Nigeria: Problems and prospects. *Educational Technology & Society*, 8(1), 104–112.

Baker, J. (2012). The technology–organization–environment framework. In Y. K. Dwivedi et al. (Eds.), *Information Systems Theory* .231–245. Springer.

Chizoma, Onyebuchi-Igbokwe, Grace. (2025). “Leveraging Artificial Intelligence (AI) Platforms to Enhance the Visibility of Local Artists in Northwest Nigeria: Opportunities and Challenges”. *Asian Journal of Education and Social Studies* 51(5):640-51. https://doi.org/10.9734/ajess/2025/51i51947.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). *User acceptance of computer technology: A comparison of two theoretical models*. Management Science, 35(8), 982–1003. <https://doi.org/10.1287/mnsc.35.8.982>.

Federal Ministry of Education (FME). (2020). *National Digital Economy Policy and Strategy (2020–2030)*. Abuja: Government of Nigeria.

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning*. Boston, MA: Center for Curriculum Redesign.

Ifinedo, P. (2011). *Internet/e-business technologies acceptance in Canada's SMEs: An exploratory investigation*. Internet Research, 21(3), 255–281. <https://doi.org/10.1108/10662241111139283>

Jankowska, M., Lopez-Carr, D., & Funk, C. (2019). *Spatial analysis for public health applications: Addressing the challenges of spatial data*. International Journal of Health Geographics, 18(1), 17. <https://doi.org/10.1186/s12942-019-0186-4>.

Jude, E. M., & Aminu, U. (2019). Spatial analysis of digital education infrastructure in Nigeria. *Nigerian Journal of Educational Technology*, 9(2), 85–96.

Kounadi, O., & Leitner, M. (2014). *Why does geoprivacy matter? The scientific publication of confidential data*. Transactions in GIS, 18(3), 512–528. https://doi.org/10.1111/tgis.12052

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence Unleashed: An Argument for AI in Education*. Pearson Education.

Okonkwo, I. R., & Ikpe, U. H. (2022). Barriers to educational technology adoption in rural Nigeria: A case study of secondary schools in Enugu State. *Journal of African Educational Research Network*, 22(1), 45–58.

Olumorin, C. O., Fakomogbon, M. A., & Yusuf, M. O. (2021). Teachers' preparedness for integrating Artificial Intelligence into Nigerian education system. *Contemporary Educational Technology*, 13(3), ep305. <https://doi.org/10.30935/cedtech/10828>

Omar, M., Kalugendo, D., & Musa, H. (2014). GIS-based analysis of educational resource allocation. *Journal of Geospatial Studies*, 2(1), 33–41.

Rogers, E. M. (2003). *Diffusion of Innovations* (5th ed.). New York: Free Press.

Tornatzky, L. G., & Fleischer, M. (1990). *The Processes of Technological Innovation*. Lexington Books.

UNESCO. (2021). *AI and Education: Guidance for Policy-makers*. Paris: United Nations Educational, Scientific and Cultural Organization. [https://unesdoc.unesco.org/ark:/48223/pf0000376709](https://unesdoc.unesco.org/ark%3A/48223/pf0000376709).

Uwakwe, A., & Okafor, N. (2021). Educational technology and regional inequality in Nigeria: The missing data dilemma. *African Journal of Policy and Practice*, 5(1), 21–34.

World Bank. (2020). *The Future of Work in Africa: Harnessing the Potential of Digital Technologies for All*. Washington, DC: World Bank Publications.

Yousef, A. M. F., Chatti, M. A., & Schroeder, U. (2020). Spatial and temporal analysis of learning data using GIS: An educational data mining approach. *International Review of Research in Open and Distributed Learning*, 21(1), 158–178.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education. *International Journal of Educational Technology in Higher Education*, 16, 39. <https://doi.org/10.1186/s41239-019-0171-0>