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Impact of Artificial Intelligence on the Performance of Nigeria's Education Sector

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Abstract

This study examines the impact of Artificial Intelligence (AI) adoption on the performance of Nigeria's education sector using an Autoregressive Distributed Lag (ARDL) model. The findings indicate that AI adoption has a statistically significant positive effect on education sector performance, with a 1% increase in AI adoption leading to a 7.87% rise in industry performance (p-value: 0.031). Additionally, AI adoption, as a proxy for the digital economy, interacts with key economic drivers to enhance sectoral growth. Specifically, direct credit to the private sector (coefficient; 2.44, p-value;0.036), gross fixed capital formation (1.20, p-value; 0.010), service sector employment (20.97, p-value; 0.038), and government expenditure (1.83, p-value;0.011) all contribute significantly to improving education sector performance. Based on these findings, the study recommends targeted policy interventions to accelerate AI adoption, expand credit access to private sector players, boost infrastructure investment, promote employment in the service sector, and increase public expenditure on education. These measures will foster sustainable AI-driven growth in Nigeria's education sector. This study contributes to the literature by providing empirical evidence on AI's role in driving education sector growth and offers actionable insights for policymakers.

Keywords: Artificial intelligence, education sector performance, ARDL model, digital economy

Impact of Artificial Intelligence on the Performance of Nigeria's Education Sector

Artificial Intelligence (AI) refers to computer systems that simulate human intelligence, enabling them to learn, reason, make decisions, and solve problems (Odeleye, 2024). This multi-disciplinary field combines machine learning, deep learning, and symbolic reasoning to create intelligent agents capable of autonomous decision-making (Russell and Norvig, 2021). Through advanced algorithms and computational power, AI systems analyze vast datasets, recognize patterns, and adapt to changing environments, driving innovations across various industries, including health-care, finance, and transportation (Goodfellow, Bengio, and Courville 2020).

McCarthy, Minsky, Rochester, and Shannon (1955) laid the foundational framework for Artificial Intelligence (AI), conceptualizing it as a field aimed at creating machines capable of intelligent behaviour. Since then, AI has evolved into a transformative force, driving innovation across industries and reshaping economic and social landscapes. Its applications extend from predictive analytics and natural language processing to autonomous systems and advanced robotics, optimizing decision-making and enhancing efficiency. In the education sector, AI is revolutionizing pedagogical methodologies, curriculum development, and institutional management. Intelligent tutoring systems, automated grading, adaptive learning platforms, and AI-driven analytics are redefining instructional delivery, expanding accessibility, and fostering personalized learning experiences. As AI continues to advance, its integration into education presents unprecedented opportunities to bridge learning disparities, improve student outcomes, and enhance the future of knowledge dissemination.

Despite its vast potential, AI adoption in Nigeria's education sector faces challenges such as limited infrastructure, inadequate funding, and regulatory constraints. This study examines the dynamic relationship between AI adoption and education sector performance in Nigeria, assessing its impact on learning outcomes and institutional effectiveness. By providing empirical evidence, the study highlights key policy interventions required to enhance AI-driven educational transformation.

The origins of Artificial Intelligence (AI) date back to the 1950s when pioneers such as Alan Turing, Marvin Minsky, and John McCarthy explored the concept of intelligent machines (Turing, 1950; Minsky and McCarthy, 1969). Over the decades, AI has evolved into a transformative technology impacting diverse industries, including healthcare, finance, transportation, and education (Brynjolfsson and McAfee, 2014; Heaton, McElvain and Wijaya, 2017; Kalantri, Khandelwal and Mahajan, 2018). AI's applications include machine learning, natural language processing, computer vision, and robotics, significantly enhancing efficiency, decision-making, and productivity (Luckin, Holmes, Griffiths, and Forcier 2016; Dziuban, Graham, Moskal, Norberg, and Sicilia 2018).

AI has revolutionized multiple sectors by enabling machines to simulate human intelligence in areas such as problem-solving, reasoning, and perception (Kurzweil, 2005; Russell and Norvig, 2010). Recent advances in AI, particularly in deep learning and natural language processing, have further expanded its potential (LeCun, Bengio, and Hinton 2015; Silver, Huang, Maddison, Guez, Sifre, Driessche and Hassabis 2016; Devlin, Chang, Lee, and Toutanova 2019). McKinsey (2022) estimated that AI could contribute $13 trillion to the global economy by 2030. These advancements have led to AI-driven innovations, such as IBM's Watson for Oncology in healthcare and AI-powered financial trading systems (Chen, Wang, and Lee, 2022). In education, AI facilitates personalized learning, intelligent tutoring, and automated assessments, improving student outcomes (Baker, 2019).

The development of AI is supported by several key technologies. Machine learning enables data-driven learning without explicit programming (Hastie, Tibshirani, and Friedman, 2019), deep learning employs neural networks to analyze complex patterns (Goodfellow et al., 2016), and natural language processing enhances human-computer interactions (Manning, 2020). AI-powered computer vision aids in visual data interpretation (Kalantri et al., 2018), while robotics integrates AI into physical systems (Khatib et al., 2019). As AI adoption increases, its impact on industries and societies will expand, with projections estimating AI could generate 97 million new jobs globally by 2025 (World Economic Forum, 2023). However, concerns persist regarding job displacement, bias, and security risks, necessitating responsible AI development (Bostrom and Yudkowsky, 2014; Jordan, 2019).

AI in Nigeria's Education Sector

Nigeria's education sector faces numerous challenges, including inadequate infrastructure, limited resources, and poor learning outcomes (Federal Ministry of Education, 2020). A shortage of qualified teachers, insufficient funding, and inefficient resource allocation exacerbate these issues (Adeyemo, 2019). UNESCO estimates that Nigeria has one of the highest numbers of out-of-school children globally, with approximately 10.5 million children not receiving formal education (UNESCO, 2020). These disparities are further pronounced between urban and rural areas (Oke, 2019). Researchers emphasize the urgent need for technological interventions, including AI, to enhance education quality and accessibility (Afolabi, 2020; Adeyemo, Olaniyan, and Ojo, M.2020). Studies indicate that AI-driven learning platforms can increase access to quality education, particularly in underserved regions (Oladele, Adebanjo, and Yusuf, 2020).

AI offers significant potential to address educational challenges in Nigeria by enabling personalized learning, enhancing teacher capacity, and optimizing resource distribution (Afolabi, 2020). AI-driven adaptive learning systems adjust to students' individual needs, improving academic performance (Dziuban et al., 2018). AI tools can also support teacher professional development through real-time feedback and mentoring (Oladele et al., 2020). AI-enabled assessments and feedback mechanisms can reduce educators' workload while enhancing student evaluations (Eweniyi, 2020). Furthermore, AI-driven virtual learning environments can promote inclusivity, providing equitable educational opportunities for disadvantaged groups, including students with disabilities and those from low-income backgrounds (UNESCO, 2020).

Research Gap and Study Justification

Despite the potential benefits of AI in Nigeria's education sector, empirical evidence on the impact of AI adoption on education sector performance remains limited. The integration of AI faces several challenges, including infrastructure deficiencies, digital literacy gaps, and weak policy frameworks. Consequently, the education sector's contribution to Nigeria's economic growth is suboptimal. This study aims to address this gap by examining the relationship between AI adoption and education sector performance in Nigeria. By employing an Autoregressive Distributed Lag (ARDL) model, the study will provide empirical insights into AI's role in driving sectoral growth, thereby informing policy interventions aimed at enhancing AI adoption and educational development in Nigeria.

Theoretical Review

Human Capital Theory:

The Human Capital Theory, formulated by Schultz (1961) and the ground-breaking work of Becker (1962;1964) gained prominence in the mid-20th century. It highlights the value of investing in human capital. The theory provides a framework to promote education, skill development, and overall human well-being as crucial drivers of economic growth. Schultz (1961) opined that education, training, and health are not merely personal services but also productive investments in human beings. The acquisition of skills and knowledge is an investment in human beings. According to Becker (1962; 1964), education, training, medical care, and information are the types of investment in human capital that can raise the earnings of individuals. "Human capital is the stock of competencies, knowledge, social and personality attributes, including creativity, embodied in the ability to perform labour so as to produce economic value." The theory posits that individuals and societies can improve their economic productivity and potential by investing in education, training, and health. These investments are referred to as "human capital." The theory underscores the link between skills and productivity. Educated and skilled individuals are more productive, which contributes to economic growth and overall development.

Human capital is seen as a productive asset that generates economic returns over an individual's lifetime. Just as physical capital (machinery, infrastructure) enhances productivity, human capital does the same through increased skills and knowledge. Human Capital Theory asserts that education is a primary way to enhance human capital. Individuals with higher levels of education tend to earn more due to increased skills and knowledge. The theory also extends to health. Healthy individuals are more productive, leading to better economic outcomes. Investments in health, such as preventive healthcare, contribute to human capital. This theory supports policies aimed at improving access to education, vocational training, and healthcare services.

Endogenous Growth Theory

Endogenous Growth Theory represents a paradigm shift by highlighting the importance of deliberate investments in human capital, innovation, and knowledge creation as drivers of economic growth (Romer, 1986; 1990) (Lucas, 1988). This theory underscores the active role of economic agents in shaping their own growth trajectory and emphasizes the potential for self-reinforcing cycles of innovation and development. At its core, this theory contends that economic growth is fuelled by internal factors, specifically focusing on human capital accumulation, technological innovation, and knowledge creation. Unlike earlier theories, which portrayed technological progress as exogenous, Romer's framework emphasizes deliberate efforts and investments in research and development (R&D) that lead to transformative growth.

A central tenet of the theory is endogenous technological change, which means that technological progress is not exogenously determined but rather endogenously generated by human effort and investments in research and development (R&D). Economic agents actively create new knowledge, ideas, and innovations to enhance productivity and drive growth technological progress is not exogenously determined but rather endogenously generated by human effort and investments in research and development (R&D). Economic agents actively create new knowledge, ideas, and innovations to enhance productivity and drive growth. It is a departure from traditional neoclassical growth theories by emphasizing the role of internal factors, particularly technological innovation and human capital, in driving sustained economic growth (Romer, 2012).

Empirical Review

Guangda Qian (2023) investigated the impact of the digital economy on rural development in China. The independent variable, digital economy, was measured using three secondary indicators; digital infrastructure, digitization of agriculture, and digital industrialization with tertiary indicators of rural internet penetration rate, rural smartphone penetration rate, and agrometeorological observatory for digital infrastructure. For digitization of agriculture; the tertiary indicators were digital scale in agriculture, digital trading of agricultural products, and investment efforts in agricultural production while for digital industrialization, rural network payment levels, rural IT applications, agricultural and rural entrepreneurship, and innovation base. For the dependent variable, rural development, the indicators were economic development, social development, living standard, and rural ecology. Using the entropy value method, they obtained the index for the digital economy and rural development, conducted a regression analysis, and found that with a 1% increase in the digital economy, rural development increased by 0.165%.

Sunita, Megha, and Aishwarya (2019) empirically investigated the impact of the digital economy on human capital development. The study analyzed how advancement in ICT could promote human capital development with special reference to South Asian Region (SAR) over the period 2000-16 by employing panel fixed effects modelling (FE-Model). Where social human capital is proxied by the Human Development Index (HDI) and ICT penetration is measured by parameters like technological readiness, mobile cellular subscriptions, and internet penetration. Other indicators of HDI used were per capita GDP, school enrolment, and life expectancy. This is supplemented by other key macroeconomic control variables like population growth, urbanization sprawl, and others to obtain an umbrella view. To have an in-depth understanding, individual component level linkages of HDI such as per capita GDP, birth life expectancy, and school enrolment rate with ICT and other macroeconomic demographic indicators are also tested separately. The empirical analysis results hint towards the strong positive associations of internet penetration, technological readiness, and mobile usage with the human development index. All

ICT infrastructure indicators; fixed broadband, mobile subscriptions, and internet penetration are found to have a positive and significant impact on all the key dependent variables, HDI and its components like net school enrolment rate, birth life expectancy, and per capita GDP.

Njoh (2018) investigated the relationship between modern information and communications technologies and development in Africa. He established a link between mobile phone subscriptions and internet access for economic development in Africa as measured by the Human Development Index (HDI). Using cross-sectional data in 2013, the results of the multiple regression analyses indicated that no such evidence was found regarding fixed phone and fixed broadband subscriptions, thus illustrating that not all types of ICT matter for economic progress.

Method

Construction of the Digital Economy Index (Proxy for AI Adoption) Using Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a widely used statistical technique for reducing dimensionality in datasets while retaining essential information (Kothari & Garg, 2014). It transforms a set of correlated variables into a smaller set of uncorrelated variables, known as principal components, which capture the maximum variance in the data. The first principal component explains the highest variance, making it the most significant factor in understanding underlying patterns within the dataset. PCA is particularly useful for index construction as it aggregates multiple indicators into a single composite measure, thereby simplifying complex relationships between variables.

Quantifying AI adoption in Nigeria's education sector requires a robust measure that captures the extent of digital transformation; therefore, the digital economy index was constructed as a proxy variable for AI adoption. This integrates key indicators across three core dimensions of the digital economy: digital infrastructure, digital industry, and digital integration (Zhang et al., 2021; Hu, 2022; Qian, 2023; Ma et al., 2023). These dimensions collectively assess AI readiness, accessibility, and utilization within the economy. The DEI is constructed using fifteen carefully selected indicators that reflect the technological capacity and digital engagement necessary for AI-driven advancements in education:

i. **Digital Infrastructure:** Mobile network coverage (3G and above), broadband subscriptions, secure internet servers, internet penetration, and electric power consumption.

ii. **Digital Industry:** High-tech exports, ICT goods exports/imports, and ICT service exports.

iii. **Digital Integration:** Share of individuals using the internet, ATM penetration, and digital financial transactions.

The PCA approach ensures that the most informative components of these indicators are retained while reducing redundancy. The **E-views statistical software** was used to compute the **eigenvalues** of each principal component, where higher eigenvalues indicate greater explanatory power. The **first principal component (PC1),** which captures the highest variance, is selected as the **Digital Economy Index (DEI)** serving as the proxy for AI adoption in Nigeria's education sector.

Justification for the ARDL Model

This study employs the **Autoregressive Distributed Lag (ARDL) model** to analyze the dynamic relationship between AI adoption (proxied by the DEI) and education sector performance in Nigeria. The choice of the **ARDL model** is justified by several advantages:

1. **Suitability for Small Sample Sizes**; ARDL performs well with limited observations, making it ideal given the available data on AI adoption in Nigeria.

2. **Flexibility in Handling Mixed Order of Integration**; Unlike traditional cointegration techniques, ARDL can accommodate variables integrated at **both I(0) and I(1)**, allowing for robust long-run and short-run estimates.

3. **Captures Both Short-Run and Long-Run Dynamics**; The ARDL approach distinguishes between immediate (short-run) effects and sustained (long-run) impacts,

providing a comprehensive understanding of AI's influence on education sector performance.

4. **Efficient in Addressing Endogeneity Issues**; The inclusion of **lagged dependent variables** helps mitigate endogeneity concerns, ensuring reliable parameter estimates.

The ARDL model is specified as follows:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_t Y_{t-1} + \sum_{j=0}^{q} \gamma_j X_{t-j} + \varepsilon_t ----3.1$$

Where: Y_t represents **education sector performance,** X_t represents **AI adoption (proxied by DEI)** and other control variables (such as government expenditure, private sector credit, and service sector employment),

α is the constant term, β_i and γ_j are the estimated coefficients, ε_t is the error term. This model allows us to examine both the **short-run fluctuations** and the **long-run equilibrium relationships** between AI adoption and education sector performance.

Data Description

The nature and sources of data play a critical role in shaping the analysis, conclusions, and recommendations of the study. Ensuring data quality, reliability, and relevance is essential for producing meaningful and insightful results. The study used secondary data from 2000 to 2023. The data were obtained from the National Bureau of Statistics(NBS), Central Bank of Nigeria (CBN), Nigerian Communications Commission (NCC), International Telecommunication Union(ITU), World Development Index(WDI), International Labour Organisation (ILO), Global Change Data Lab, and Internet World Stats

Modelling (Model Specification)

In line with the theoretical framework of the Endogenous Growth Model underpinning this study, the empirical models of James et al., (2023) and **Zhang et al., (2021)**, the index of WEF (2018) Solomon and Klyton (2020), modified and extended with digital economy index, DEI, a proxy for AI adoption in Education sector, the sector's growth, the indicator of its performance (InEdu) and the models are thus specified:

$$GDP = A * K^{\alpha} * H^{\beta} \quad (3.2)$$

$$\text{InEdu} = \alpha_0 + \beta_1 Ingdp + \sum_{1=i}^{n} \lambda\Delta + \varepsilon_t \quad (3.3)$$

Expanding equation 3.2 with control variables; GDP growth (GDP), domestic credit to private sector (DCP), population growth (POP), trade openness (TO), GNE (Gross National Expenditure), inflation (INF), human capital development (HC), GFKF (Gross Fixed Capital Income) and FDI through the external demand shock term to yield a standard ARDL model in equation 3.3 as follows;

$$SG_{edu} = \rho_0 + \rho_1 DEI + \rho_2 HDI + \rho_3 DCP + \rho_4 GFCF + \rho_5 RCGF + \rho_6 GE + \rho_7 SSE + \rho_8 SSE + \rho_9 SSE + \varepsilon \quad (3.4)$$

$$LSSG_{it} = \Upsilon_0 + \Upsilon_1 LSSG_{i,t-1} + \Upsilon_2 DEI_{1,i,t-1} + \Upsilon_3 DCP_{1,i,t-1} + \Upsilon_4 GFCF_{1,i,t-1} + + \Upsilon_5 RGCF_{1,i,t-1} + \Upsilon_6 GE_{1,i,t-1} + \Upsilon_7 SSE_{1,i,t-1} + \Upsilon_8 HDI_{1,i,t-1} + \Upsilon_9 LFR_{1,i,t-1} + \Upsilon_{10} TFP_{1,i,t-1} + \sum_{j=1}^{q-1} \alpha_1 \Delta LSSG_i + \sum_{j=1}^{q-1} \alpha_2 \Delta DEI_i + \sum_{j=1}^{q-1} \alpha_3 \Delta DCP_i + \sum_{j=1}^{q-1} \alpha_4 \Delta GFCF_i + \sum_{j=1}^{q-1} \alpha_5 \Delta RGCF_i + \sum_{j=1}^{q-1} \alpha_6 \Delta GE_i + + \sum_{j=1}^{q-1} \alpha_7 \Delta SSE_i + \sum_{j=1}^{q-1} \alpha_8 \Delta HC_i + \sum_{j=1}^{q-1} \alpha_9 \Delta LFR_i + \sum_{j=1}^{q-1} \alpha_{10} \Delta TFP_{i,} + \lambda ETC_i + \varepsilon_{it} \quad (3.5)$$

Where:

SSG is service sector growth, SG_{ic} is Information and Communication, Finance and Insurance, Professional, Scientific & Technical Services, Education, DEI is the digital economy index, HDI is human capital development, GFCF is the gross fixed capital formation and RGCF is capital formation growth rate, SSE is service sector employment, NE is government expenditure, DPC is a direct credit to private sector, LFR is labour force rate, TFP is Total factor productivity.

Dependent Variable: EDU_GROWTH				
Method: ARDL				
Date: 08/31/24 Time: 18:12				
Sample (adjusted): 2001 2023				
Included observations: 23 after adjustments				
Maximum dependent lags: 1 (Automatic selection)				
Model selection method: Akaike info criterion (AIC)				
Dynamic regressors (1 lag, automatic): DCP DEI GFCF SSE GE HDI LFR				
RGCF TFP SVA				
Fixed regressors: C				
Number of models evaluated: 1024				
Selected Model: ARDL(1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.*
EDU_GROWTH(-1)	0.132723	0.053328	2.488826	0.0886
DCP	2.444862	0.670218	3.647858	0.0355
DEI	7.871740	2.044930	3.849393	0.0310
DEI(-1)	2.347492	1.768160	1.327647	0.2763
GFCF	-0.792466	0.153569	-5.160319	0.0141
GFCF(-1)	1.200318	0.204535	5.868507	0.0099
SSE	20.96881	5.921228	3.541295	0.0383
SSE(-1)	-8.042240	4.866050	-1.652724	0.1970
GE	1.829746	0.324950	5.630848	0.0111
GE(-1)	0.932067	0.273128	3.412571	0.0421
HDI	-1536.827	254.7749	-6.032098	0.0091
LFR	-1068.850	1158.240	-0.922823	0.4242
LFR(-1)	-8725.639	1624.313	-5.371896	0.0126
RGCF	1.190269	0.551567	2.157977	0.1198
RGCF(-1)	-1.006211	0.711859	-1.413498	0.2524
TFP	-58.60580	40.25524	-1.455855	0.2415
TFP(-1)	381.6583	64.50154	5.917041	0.0096
SVA	-1.77E-11	5.44E-11	-0.324562	0.7668
SVA(-1)	-6.04E-10	1.07E-10	-5.658860	0.0109
C	2967.509	609.6320	4.867706	0.0166
R-squared	0.992181	Mean dependent var		12.88147
Adjusted R-squared	0.942661	S.D. dependent var		9.004502
S.E. of regression	2.156177	Akaike info criterion		4.076799
Sum squared resid	13.94729	Schwarz criterion		5.064185
Log likelihood	-26.88319	Hannan-Quinn criter.		4.325124
F-statistic	20.03598	Durbin-Watson stat		2.681353
Prob(F-statistic)	0.015203			
*Note: p-values and any subsequent tests do not account for the model selection.				

Source: Author's Computation, 2024 using E-views 10

The results of the ARDL long-run dynamics model provide significant insights into the determinants of education sector growth (EDU_GROWTH) in Nigeria. The high R-squared value (0.9922) and adjusted R-squared (0.9427) indicate that the model explains a substantial proportion of the variation in EDU_GROWTH. Additionally, the F-statistic (20.036, p-value = 0.0152) confirms the overall statistical significance of the model. However, a closer examination of the coefficients and their economic implications is essential to align these results with the study's objectives.

The Digital Economy Index (DEI) exhibits a strong positive relationship with EDU_GROWTH, as indicated by its significant coefficient (7.8717, p-value = 0.0310). This suggests that digital transformation plays a crucial role in enhancing education sector growth. However, the lagged effect of DEI (2.3475, p-value = 0.2763) is statistically insignificant, implying that while digitalization has an immediate impact on the education sector, its long-term effects may be influenced by other structural factors. The importance of digital integration in education, particularly in expanding access and improving learning outcomes, is evident from these findings.

Gross Fixed Capital Formation (GFCF) presents an interesting dynamic. In the short run, the coefficient is negative (-0.7925, p-value = 0.0141), suggesting that capital investment in infrastructure and other fixed assets may initially divert resources away from immediate education sector growth. However, the lagged coefficient (1.2003, p-value = 0.0099) turns positive and significant, highlighting the long-term benefits of sustained capital investments in the sector. This result underscores the importance of patience in capital-intensive education reforms, where the benefits of infrastructure investments materialize over time.

The findings also reveal a strong relationship between service sector employment (SSE) and education sector growth. The significant coefficient (20.9688, p-value = 0.0383) suggests that increasing employment in the service sector drives EDU_GROWTH, likely by creating demand for higher education and specialized skills. However, the lagged effect of SSE (-8.0422, p-value =

0.1970) is negative but statistically insignificant, indicating that while immediate employment expansion supports education growth, long-term sustainability may depend on the quality and stability of these employment opportunities.

Government expenditure (GE) emerges as a key determinant of education sector growth, with both its immediate (1.8297, p-value = 0.0111) and lagged (0.9321, p-value = 0.0421) effects being positive and statistically significant. This reinforces the argument that public investment in education plays a crucial role in sustaining growth. However, the impact of the Human Development Index (HDI) is unexpectedly negative (-1536.827, p-value = 0.0091). This counterintuitive finding suggests that while overall human development is improving, the direct benefits to the education sector may be hindered by inefficiencies, policy misalignment, or unequal access to education resources.

Labour force participation (LFR) presents a challenge, with its lagged coefficient (-8725.639, p-value = 0.0126) indicating a significant negative impact on education growth. This suggests that a growing labor force might be drawing individuals away from formal education, particularly in a developing economy where economic survival often takes precedence over educational attainment. Similarly, total factor productivity (TFP) does not show a short-term effect, but its lagged coefficient (381.6583, p-value = 0.0096) is highly significant and positive, emphasizing the role of long-term productivity gains in driving education sector growth. These findings provide empirical support for policies that enhance digital economy adoption, increase targeted government spending, and optimize private-sector credit allocation to drive sustainable growth in the education sector. The results also highlight the need for improving sectoral productivity and ensuring labour market alignment with education sector demands.

Table 4.2

ARDL Short-Run Dynamics

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(DEI)	7.291988	2.472923	2.948732	0.0319
D(DCP)	-2.769159	0.717302	-3.860523	0.0119
D(GE)	0.725051	0.152003	4.769965	0.0050
D(GFCF)	0.160598	0.116311	1.380772	0.2259
D(HDI)	1554.831640	352.392571	4.412215	0.0069
D(LFR)	-1632.335599	972.605319	-1.678312	0.1541
D(RGCF)	0.719780	0.575605	1.250476	0.2665
D(SSE)	26.814059	4.405407	6.086625	0.0017
D(SVA)	-0.000000	0.000000	-4.432731	0.0068
D(TFP)	-401.971370	77.420096	-5.192081	0.0035
CointEq(-1)	-0.974381	0.052777	-18.462133	0.0000

Source: Author’s Computation, 2024 using E-views 10

Interpretation of Short-Run Effects

Table 4.2 presents the short-run dynamics from the ARDL model, the estimated coefficients indicate immediate impacts rather than long-term relationships. The significance and direction of these effects provide crucial insights into how various factors influence EDU_GROWTH in the short term. Digital Economy Index (DEI) (p-value;0.0319), a positive and significant short-run impact suggests that improvements in digital infrastructure and digital economy activities immediately contribute to educational sector growth. This may be due to the rapid adoption of digital learning platforms, increased access to educational resources, or ICT-driven teaching improvements. Digital Connectivity Proxy (DCP) (p-value; 0.0119), the negative and significant effect in the short run suggests that an increase in digital connectivity alone does not automatically lead to positive educational outcomes. Potential explanations include digital distractions, inadequate digital literacy, or unequal access to technology.

Government Expenditure (GE) (p-value;0.0050), the strong positive short-run effect indicates that immediate increases in public spending have a direct and significant impact on educational sector expansion. This may reflect the quick effects of policies such as school infrastructure improvements, teacher training programs, or scholarship allocations. Gross Fixed Capital Formation (GFCF) (p-value;0.2259, insignificant) while capital investment is essential for long-term educational growth, the insignificance in the short run suggests that infrastructure developments or physical investments take time to translate into measurable improvements in the education sector.

Human Development Index (HDI) (p-value; 0.0069, the strong positive coefficient confirms that overall improvements in human development such as health, income, and living conditions immediately boost education sector growth, possibly by increasing school attendance and improving learning conditions. Labour Force Participation Rate (LFR) (p-value; 0.1541p, insignificant), the negative but insignificant coefficient suggests that changes in labour force participation do not immediately affect educational growth.

The Error Correction Term (CointEq (-1)) is highly significant and negative ($p<0.0001$, coefficient = -0.974). This confirms that any short-run deviations quickly adjust toward long-run equilibrium at a rate of 97.4% per period. A near-unit speed of adjustment indicates that shocks to the education sector correct themselves almost immediately, ensuring long-run stability. The results confirm that digital economy growth and government expenditure have strong immediate positive effects on the education sector. Digital connectivity, sectoral value-added shifts, and total factor productivity may have counterintuitive short-run effects, suggesting the need for further structural adjustments. The error correction term is highly significant, emphasizing that while short-run fluctuations exist, the system remains stable and corrects itself toward long-term educational growth.

The Digital Economy Index (DEI) has a statistically significant and positive effect on EDU_GROWTH in the current period (p-value; 0.0310), suggesting that digital infrastructure and integration contribute to education sector growth. However, the lagged DEI is not significant (p-value; 0.2763), indicating that its impact is more immediate rather than persistent. You should discuss why this might be the case. Government Expenditure (GE) is significant both in the current period (p-value; 0.0111) and lagged (p-value; 0.0421), indicating a sustained influence on education growth.

The negative and significant effects of the Human Development Index (HDI) and Labour Force Participation Rate (LFR) on education sector growth suggest that broader improvements in human development and workforce participation do not necessarily translate into educational expansion. This could be due to structural challenges such as skill mismatches, inadequate educational infrastructure, or barriers that prevent increased labour force engagement from directly benefiting the education sector. Additionally, while HDI captures overall well-being, it does not specifically account for investments in education, and a higher LFR might indicate greater workforce absorption in other sectors rather than education-related employment growth.

The findings on Total Factor Productivity (TFP) indicate a significant positive lagged effect, implying that productivity improvements take time before they manifest as educational sector expansion. This suggests that while technological and efficiency advancements contribute to long-term educational development, the immediate effects may not be visible due to the time required for policy adaptation, institutional adjustments, and resource allocation. R-squared value of 0.9922 indicates that 92% of the variation in Nigeria's education sector was explained by AI adoption and other independent variables.

Discussion

The positive coefficient of lagged education sector growth, though statistically insignificant (0.132723, p-value: 0.0886), suggests that past growth trends positively influence current expansion. This aligns with prior research on education sector persistence, where previous investments and institutional improvements contribute to sustained development. The statistically significant positive coefficient of direct credit to the private sector (2.444862, p-value: 0.0355) underscores the role of the financial sector deepening in fostering education sector growth. This result is consistent with studies highlighting how increased private sector credit stimulates investments in education infrastructure, including private schools and higher education institutions. Policy measures aimed at expanding access to education-specific credit facilities could enhance this effect further.

AI adoption demonstrates a strong and positive impact on education sector growth (7.871740, p-value: 0.0310), reinforcing the significance of the digital economy in driving sectoral transformation. The result suggests that increased AI integration across various educational levels—such as adaptive learning technologies, AI-driven content delivery, and smart classrooms—can significantly enhance sectoral output. This finding aligns with global trends, where AI adoption has been linked to improved learning outcomes, operational efficiencies, and broader access to quality education. Policymakers should prioritize AI-driven education reforms to maximize its growth potential.

Gross fixed capital formation exhibits contrasting short- and long-run effects, with a negative and statistically significant coefficient in the current period (-0.792466, p-value: 0.0141) and a positive long-run effect (1.200318, p-value: 0.0099). This suggests that while immediate capital expenditures may be associated with high costs or inefficiencies, their benefits materialize over time as infrastructure investments yield returns. The findings emphasize the importance of sustained capital investment in education facilities, ensuring that short-term financial constraints do not undermine long-term growth potential.

Service sector employment significantly contributes to education sector growth (20.96881, p-value: 0.0383), indicating that job creation in the education sector has a strong multiplier effect. The result suggests that increasing employment opportunities within the education sector, through teacher recruitment, administrative expansions, and skill development programs can drive substantial sectoral growth. This aligns with studies emphasizing the role of human capital in fostering industry expansion. Policymakers should consider workforce development initiatives and targeted employment policies to sustain growth momentum.

The digital economy, with a positive and significant coefficient (7.291988, p-value: 0.0319), further reinforces the transformative role of digitalization in education. The short-run effect highlights the immediate benefits of digital technologies in enhancing learning experiences, administrative efficiencies, and accessibility. The integration of digital platforms, e-learning resources, and AI-driven educational tools can further amplify this impact. Policies should focus on bridging digital divides and ensuring that educational institutions have access to the necessary digital infrastructure.

Short-run adjustments reveal that education sector growth responds rapidly to deviations from its long-run equilibrium. The error correction term (CointEq (-1)) is negative and highly significant (-0.974381, p-value: 0.0000), indicating that approximately 97.4% of disequilibrium is corrected within one period. This suggests a highly responsive system where policy interventions and structural adjustments can quickly restore stability. Compared to similar economies, this speed of adjustment highlights the resilience of Nigeria's education sector to external shocks and policy changes. Further research could explore the specific mechanisms that facilitate this rapid correction.

Overall, the findings align with existing literature while providing new empirical evidence on the role of AI adoption, financial deepening, and employment in driving education sector growth. The results suggest that a combination of digital economy integration targeted financial policies, and sustained capital investments can create a robust foundation for sectoral expansion.

Policymakers should leverage these insights to design effective interventions that enhance the education sector's performance and long-term sustainability.

Conclusion

The study establishes a clear link between AI adoption and education sector growth in Nigeria, demonstrating that AI is a transformative driver of sectoral expansion. The findings highlight the need for strategic policies and investments to maximize AI's potential in fostering sustainable growth, innovation, and social impact. By providing empirical evidence on AI's role in education sector performance, this research contributes to existing literature and offers valuable insights for policymakers, educators, and industry stakeholders. The results underscore AI's catalytic effect on education, reinforcing the urgency of integrating digital technologies to enhance learning outcomes, institutional efficiency, and workforce development.

Recommendations

Optimizing AI adoption in Nigeria's education sector requires well-defined implementation strategies across key intervention areas. Educator training programs should be established through public-private partnerships, integrating AI literacy into teacher certification curricula and continuous professional development. Collaborations with global EdTech firms can provide scalable AI-powered training modules tailored to Nigeria's educational needs.

Enhancing digital infrastructure demands targeted investments in broadband expansion, cloud-based learning platforms, and AI-integrated smart classrooms. The government should incentivize private sector participation through tax breaks and subsidies, fostering innovation in digital learning environments.

Expanding private-sector credit for AI-driven education initiatives can be achieved by introducing low-interest loans and grant schemes specifically for EdTech startups. Financial institutions should collaborate with education ministries to design AI-focused funding models that encourage innovation in adaptive learning technologies.

Strengthening gross fixed capital formation in education infrastructure necessitates a multi-stakeholder approach. Prioritizing AI-enabled facilities, such as smart libraries and interactive learning hubs, will enhance digital literacy and student engagement. Public-private partnerships can accelerate investment in AI-driven curriculum development and content creation.

Promoting employment in the education sector through AI integration requires comprehensive teacher training and incentives for AI specialization. Scholarships and funding should be allocated to attract educators to AI-related fields, while AI-powered teaching assistants can help bridge gaps in resource-limited areas.

Government expenditure on AI-driven education initiatives must be strategically allocated to support digital literacy programs, AI curriculum integration, and nationwide deployment of smart learning tools. Establishing a national AI in Education Task Force will ensure policy alignment, monitoring, and continuous improvement. By implementing these targeted strategies, Nigeria can fully leverage AI's transformative power to enhance education quality, drive economic growth, and ensure long-term sectoral sustainability.

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