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IMPACT OF DIGITAL INFRASTRUCTURE ON HUMAN CAPITAL DEVELOPMENT IN NIGERIA

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Abstract *Digital infrastructure distribution inequities pose a major global challenge, blocking access to education, workforce development, and economic possibilities, specifically affecting developing nations. As a result, understanding how digital infrastructure influences human capital development has gained importance for nations that aim to eliminate digital disparities. This study investigates the effect of digital technology infrastructure on human capital development in Nigeria, using the Autoregressive Distributed Lag (ARDL) framework to assess the effect of digital infrastructure, economic growth, trade openness and population on human capital development. Analysis of both short-term and long-term digital infrastructure effects on human capital development is based on secondary data that spans from 1986 to 2022. The results show that digital infrastructure exerts statistically positive long-term effects on Nigeria's human capital development. However, short-term disruption was noticed in the first lag, where digital infrastructure showed a negative effect, while the third lag exhibited positive and significant effects. The study concluded that digital infrastructure exerts significant positive and long-term effects on human capital development in Nigeria. Therefore, the study recommends that Government policy needs to focus on building broadband infrastructure networks in areas with limited coverage, such as rural zones, through public-private partnerships with telecom providers, and there is a need to reduce internet service costs by implementing supportive regulations and infrastructure subsidies, which will expand digital learning access as well as create skilled Nigerian workers. These strategic interventions will boost the long-term effect of digital infrastructure on human capital growth and position Nigeria for better economic results in the digital economy.*

Keywords ARDL Model, Digital Technology, Human Capital Development, Infrastructure

1.0 Introduction

Digital infrastructure has emerged as a driver of globalisation and socio-economic development due to its effect on education, workforce productivity, and innovation. The foundational base of the digital economy that enables the progress of human capital are broadband networks, digital platforms and mobile technology. Globally, countries are utilising digital infrastructure to close educational disparities, improve skill acquisition, and prepare their workforce for the needs of a digitalised economy. For example, developed countries with well-established digital environments apply technology to make distance learning and workforce training complementary to making labour markets more responsive and creative (Davidson et al., 2023). Similarly, emerging economies in Asia and Latin America have adopted digital platforms to expand educational access and support entrepreneurship, creating more equitable opportunities for underserved populations (Das & Nanga, 2022; Pigola et al., 2024).

The relationship between digital infrastructure and human capital development is less consistent in sub-Saharan Africa. Countries such as Kenya and Rwanda have demonstrated the potential of digital infrastructure to foster innovation and improve digital literacy through significant investments in ICT (Barasa, 2021). However, many nations in the region face challenges such as unreliable connectivity, insufficient funding, and limited digital skills, which hinder fully realising digital infrastructure's potential. Despite these challenges, the role of digital technology in reducing barriers to education and enabling workforce development is increasingly recognised in the region (Gbadebo, 2024).

Nigeria holds immense potential for leveraging digital infrastructure to advance human capital development. With a rapidly growing population and an increasing demand for digital skills in the labour market, the country stands at a critical juncture. Recent initiatives such as the National Digital Economy Policy and Strategy by the Federal Ministry of Communications and Digital Economy have aimed to enhance internet penetration, expand digital literacy, and create technology-driven opportunities for its workforce (Federal Ministry of Communications and Digital Economy, 2023). Despite these efforts, Nigeria faces persistent challenges, including unreliable internet access, limited rural connectivity, and inadequate infrastructure funding, which undermine its ability to harness the benefits of digital infrastructure (Davidson et al., 2023).

Moreover, studies have demonstrated that digital infrastructure has a significant short-term impact on human capital outcomes, particularly in expanding access to education and improving workforce skills (Chen et al., 2023). However, the long-term effects of digital technology infrastructure remain uncertain, especially in Nigeria, where socio-economic disparities and infrastructural deficits persist. Furthermore, much of the existing research focuses on macroeconomic benefits, such as GDP growth and trade openness, while neglecting direct outcomes related to human capital, such as educational attainment and workforce readiness (Chiemeke & Imafidor, 2020). Addressing this gap is crucial for understanding how digital infrastructure can be leveraged to maximise its impact on human capital development in Nigeria.

Therefore, this paper seeks to investigate the effects of digital technology on human capital development in Nigeria. To achieve the study's aim, the subsequent section presents a literature review, which include theoretical framework and empirical review on digital technology transformation of various industries and human capital formation, and the method section describes the estimation and data collection techniques used in the study. The results presentation, conclusion, and recommendation conclude the study.

2.0 Literature Review

This section consists of a theoretical review blended with a framework and empirical review to provide a basis for the effect of digital infrastructure on human capital development in Nigeria.

2.1 Theoretical Review

Strong theoretical principles serve as the basis for comprehending how digital infrastructure affects human capital development in Nigeria. This study uses three important economic theories to explain the effects of digital infrastructure on human capital development. The theories include the Keynesian economic theory, the Solow growth model, and the endogenous growth theory. The Keynesian economic theory depends on both public sector involvement and aggregate demand for achieving economic growth. Keynes (1936) demonstrated that public spending accompanied by public investments activates aggregate demand, leading to higher employment and increased economic productivity. Digital infrastructure investment made by governments through digital technology expansion programs like broadband access, educational platforms and

ICT infrastructure systems boost aggregate demand by improving training programs and developing digital competencies (Davidson et al., 2023).

Human capital development becomes possible because of this process, which is an essential requirement for economic growth. Digital infrastructure also develops new employment opportunities within the technology and education sectors, stimulating consumer expenditure and market demand. Digital technology-driven productivity improvements through better connection networks, faster information acquisition, and optimised work procedures produce higher economic outputs. According to the Keynesian model, government funding for digital infrastructure constitutes a purposeful action that simultaneously minimises education inequality and generates economic development through market expansion alongside labour force efficiency improvement (Das & Nanga, 2022).

Moreover, the Solow growth theory shows that technological advancements function as the main force sustaining enduring economic growth. According to Solow (1956) the fundamental components contributing to economic growth include capital growth, workforce growth and technological development. Investments in education and technological advancements enhance human capital, which results in increased productivity. Digital platforms and broadband networks, together with mobile technology, create the fundamental base for digital education, which permits users to gain educational materials while taking e-learning classes and learning digital skills (Pigola et al., 2024). Modern technological advancements drive human capital productivity according to the principles established by Solow in the study of technological progress. The long-term growth of total factor productivity and economic growth results from digital infrastructure providing access to information and digital tools, which encourages innovation and entrepreneurship activities (Chen et al., 2023).

In addition, the endogenous growth model established by Romer (1986) and Lucas (1988) recognises human capital development, innovation, and knowledge accumulation as fundamental elements of economic expansion. According to the endogenous growth theory, technology and human capital exist as endogenous elements that drive continuous economic growth through knowledge spread and creative production. The digital infrastructure system speeds up human capital development using educational tools which include digital

learning technologies as well as virtual education spaces and internet-based training opportunities (Eke, 2023). Therefore, Investments in human capital through education produce higher productivity which drives sustained economic growth. Digital platforms also promote knowledge spillovers through their capabilities in information sharing, collaboration and innovation facilitation in accordance with endogenous growth models (Davidson et al., 2023).

Endogenous growth theory provides improved insight into the Solow growth model by making technological progress internal to its framework. It also concurrently expands Keynesian thinking by focusing on human capital development and innovative practices for economic advancement. The theory demonstrates how digital infrastructure drives knowledge-sharing processes that lead to innovative entrepreneurship, which results in complete human capital system understanding. The interconnected theory shows how digital infrastructure activates aggregate demand. At the same time, it supports increased productivity while simultaneously promoting sustainable economic growth from innovative human capital expenditure. It, therefore, serves as the theoretical framework for this study.

2.2 Empirical Review

The literature offers empirical evidence regarding related dynamics in digital infrastructure and human capital development. For example, Alabbas et al. (2024) analysed the relationship between gross Domestic Product (GDP), Information communication technology (ICT), education enrolment and labour force in Nigerian from 1991 to 2021 using the Autoregressive Distributed Lag (ARDL) model. From their findings, ICT and tertiary education enrolment have positive and significant impacts on GDP both in the short run and in the long run, while secondary school enrolment and gross capital formation also positively affect GDP, though with low impressive impacts. Likewise, Kichurchak, (2024) uses pooled regression, fixed-and random-effect estimations in the panel data analysis that covers 21 EU countries between 2013 and 2021. Their result also shows that public expenditure on higher education, the state of the labour market, and environmental taxes improve human capital, and fixed-effect estimators offered the best results.

With a focus on education, technology, and growth, Eke, (2023) focuses on the impact of digital technologies, including e-learning systems and telemedicine, on economic growth in Nigeria. Adopting qualitative approaches, the study established that

infrastructural factors like erratic electric power supply and weak internet connectivity pose challenges to the optimal use of digital technology in Nigeria. In addition, Eva et al. (2021) apply descriptive analysis and time series analysis to explore the connection of digitisation to human capital development. They noticed considerable delays in digitisation and education than their counterparts in Western Europe. It is also noteworthy that both works highlight the need for strategic procurement of digital resources and systems and overall changes to establish the Socio-Technical Divide.

Moreover, technology also affects economic development, as pointed out by Origin et al. (2024). They use the ARDL model to estimate an empirical model of fintech in Nigeria between 2006 and 2022. Based on their research, they discovered that the use of other innovations such as ATMs, POS, Internet and mobile banking have not significantly affected the HDI. They attribute this to infrastructure challenges and poor penetration in rural areas. In addition, Lawal et al. (2024) conducted an ex post facto study and applied OLS analysis to measure the effect of private sector technology investment on Nigerian GDP from 1999 to 2022. They study provides evidence of a unidirectional Granger causality from Technology investment to GDP growth. In analysing human development beyond the HDI indices, (Azeez & Zhengzhou, 2024) investigate the impact of the index of economic activity- GDP, population growth, fertility rates, devaluation and inflation rate on Nigerian HDI using the ARDL model for the time series data for 1988 to 2022. The results reveal that fertility rates play a negative role in determining HDI, while GDP and inflation do not, in fact, play an insignificant effect on HDI.

Chen et al. (2023) also examine the effect of digital servitisation and infrastructure development on sustainability and financial performance among Chinese manufacturing firms. They utilise panel vector autoregression (PVAR) on 1,083 firms from 2014 to 2019, and to their observations, they confirm that digital infrastructure always increases operational efficiency, and digital servitisation, in particular, improves financial performance for environment-leadership companies. Similarly, Wang and Si (2024) use both quantitative and qualitative approaches to assess the performance of libraries in the provision of digital opportunity and teaching of digital literacy in China. Their findings indicate that libraries are crucial in closing the digital gap and enabling distressed communities to benefit from basic digital literacy skills.

Furthermore, Jayadevan et al., (2024) study the effect of Innovation on economic globalisation in escaping the middle-income trap using data of 27 countries between 1990 and 2019. They applied Bayesian Model Averaging (BMA) and Cox regression. Three variables, namely internet usage, trade openness and labour Productivity, are established as drivers of economic growth and fast transitional movement to high-income level nations. Altogether, these papers prove the interdependence of education, digital infrastructure, financial technology, and innovation in supporting sustainable development while solving economic issues. However, with the increase in the understanding of digital technology infrastructure as a globally transformational element of socio-economic development and evidence of a robust digital infrastructure, there is very limited research on the direct effects of digital technologies on human capital development in Nigeria.

3.0 Methodology

The model used to determine the effect of digital technology on human capital is adapted from the study of Azeez and Zhengzhou, (2024), where human development was modelled as a function of selected macroeconomic variables. However, to achieve the objective of this study digital technology is added to the independent variables. Therefore, the current model for the study is:

HCD = f (EG, POP, OPEN, DT) ……
…….. 1

The empirical model, therefore, is as follows:

$HCD = \beta 0 + \beta_1(EG) + \beta_2 LOG(POP) + \beta_3 LOG(OPEN) + \beta_4 LOG(DT) + \mu$…… 2

Where:

β_0= intercept

β_1, β_2, β_3, β_4,& β_5 = parameters

The data for this study was from secondary sources as it suits the nature of the study, covering the period (1986-2022). The sources and measurement of the variables are presented in Table 1

In addition, this study employs the following techniques in obtaining the numerical values for the estimates of the parameters in the linear regression models. These include the Unit root test, Bound Test, and Autoregressive Distributed lag techniques. The Unit root test is derived from the fact that estimating a model in the presence of non-stationary time series variables usually leads to spurious (meaningless) regression output, while the bound test establishes the long-run and short-run relationship between the dependent and independent variable is estimated using the bounds testing or

Autoregressive Distributed Lag (ARDL) cointegration procedure.

The estimation process after formulating equation 2 was done by employing the Autoregressive Distributed Lag (ARDL) model. This method was chosen because it benefits the establishment of the trends of the variable relationships.

Table 1: Measurement and source of data

S/N	Abbreviation	Variable Use	Proxy/Measurement	Apriori Expectation	Sources
1	HCD	Human Capital Development	Human Capital Index	Dependent variable	World Bank
2	EG	Economic Growth	GDP per capita	Positive (+)	World Bank
3	POP	Population	Population Index	Negative (-)	World Bank
4	OPEN	Openness	Export plus Import/ GDP	Positive (+)	CBN Bulletin
5	DT	Digital Infrastructure	Average of total Fixed broadband, mobile subscription and Internet users	Positive (+)	World Bank

Source: Authors' 2024

4.0 Presentation and Analysis of Results

This section presents the study's findings. It encompasses the dataset's descriptive statistics, the results from the unit root tests, the bounds test, and the ARDL estimation results. The descriptive statistics results are presented in Table 2.The results of the L(HCD), EG, L(POP), OPEN, and L(DT) exhibit different trends of central measure, variability and distributional nature. L(HCD) and EG have negative skewness, meaning they are skewed to the left and depart from normality, as shown by their Jarque Bera test. The statistical analysis of the frequency distribution indicated that LOG(POP) had a more stable distribution measure with low standard deviation and tested for near normal distribution, while OPEN had high variability but was closer to the normal distribution. Based on these results, it can be stated that LOG(DT) has a moderate level of fluctuation around its mean value while, at the same time, it has a slightly right-skewed distribution that is not very far from normal.

Table 2: Descriptive Statistics

	LOG(HCD)	EG	LOG(POP)	OPEN	LOG(DT)
Mean	4.077467	3.904725	18.66407	34.80806	12.91819
Median	4.094178	4.430627	18.65958	34.32000	12.86369
Maximum	4.114311	15.32916	19.11863	53.28000	14.33904
Minimum	3.987316	-10.92409	18.21548	9.140000	11.58202
Std. Dev.	0.039876	4.630572	0.270921	10.18611	0.760763
Skewness	-1.100055	-0.503958	0.026251	-0.325021	0.305478
Kurtosis	2.627813	4.855799	1.812504	2.856038	2.115598
Jarque-Bera	7.468512	6.689825	2.119355	0.664918	1.733152
Probability	0.023891	0.035263	0.346568	0.717158	0.420388
Sum	146.7888	140.5701	671.9066	1253.090	465.0547
Sum Sq. Dev.	0.055654	750.4768	2.568931	3631.492	20.25660
Observations	36	36	36	36	36

Source: Authors' computation, 2024

In addition, Augmented Dickey-Fuller test was adopted to test for the null hypothesis of unit root tested against the alternative of no unit root at a 5% level of significance if the null hypothesis is rejected, it can be concluded that the variables are stationary at levels. The results of the unit root test are presented in Table 3.The augmented Dickey-Fuller (ADF) test result shows that all the variables are stationary at level except for HCD which is stationary at first difference.

Table 3: Unit Root Test (ADF) Result

VARIABLE	ADF TEST STATISTICS (LEVEL)	ADF TEST STATISTICS (FIRST DIFFERENCE)	5% CRITICAL VALUE	ORDER OF INTEGRATION
LOG(HCD)	-1.362922	-3.364448	-2.948404	I (1)
EG	-5.076444	-	-2.945842	I (0)
OPEN	-4.727092	-	-2.948404	I (0)
LDT	-2.672623	-	-2.948404	I (0)
LPOP	-3.576597	-	-3.557759	I (0)

Source: Authors' computation, 2024

The best ARDL model was also determined using the Akaike Information criteria (AIC). The result is shown in Figure 1. The AIC values, which account for the goodness of the fit while considering model complexity, are given on the vertical axis. The lower the value, the better the model's performance. On the horizontal axis, it presents the ARDL model specifications, which stand for different combinations of lags. The AIC values for the best models are very similar; this means that the different model

specifications are equivalent with regard to the fitting ability. Hence, the best-fitting model seems to be ARDL (3, 0,0,0 4) because it exhibits the smallest AIC value out of all models considered in the study.

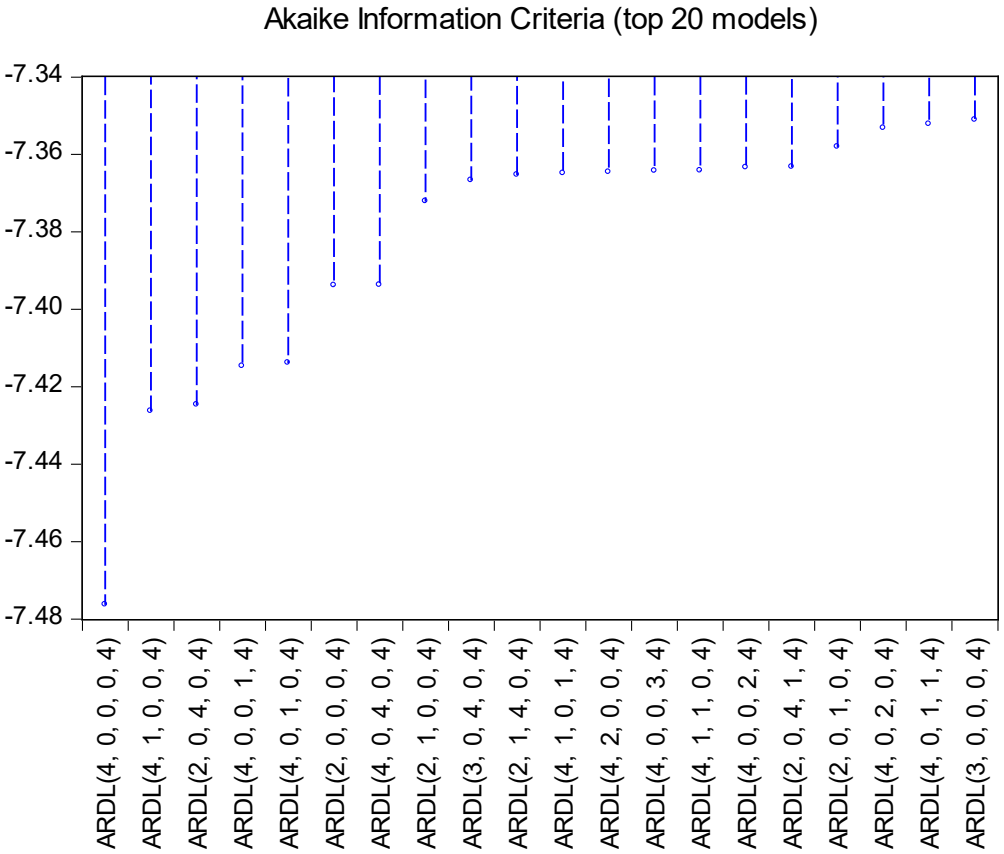


Figure 1: Lag Length Determination
Source: Author's computation, 2024

Table 4 presents the results of the bound test for the long-run cointegrating relationship among the variables in the model. The null hypothesis, which suggests that no long-run relationships are present, is compared to an alternative hypothesis, which says the opposite. The result shows the following F-statistic of the test: F = 10.33583, which is more than the I1 Bound at 10%, 5%, 2.5% and 1% significance levels. In particular, at the 1% significance level, the upper bound of the F-statistic is 5.06, significantly less than the computed F-statistic. Therefore, following the critical values of the F-statistic with all the degrees of freedom values above the upper bound across different levels of significance, the null hypothesis is rejected, which in turn exhibits the evidence of long-run co-integration among the variables of the model.

Table 4: ARDL Bounds Test

Test Statistic	Value	k
F-statistic	10.33582	5
Critical Value Bounds		
Significance	I0 Bound	I1 Bound
10%	2.45	3.52
5%	2.86	4.01
2.50%	3.25	4.49
1%	3.74	5.06

Source: Authors' Computation (2024)

4.1 Presentation of ARDL Model Results

Having established the presence of a long-run relationship between the dependent and independent variables, the ARDL method was applied to estimate both the short-run and long-run parameters. The short-run results of the nexus between the dependent and independent variables estimated using the ARDL (autoregressive distributed lag) approach are presented. The lag length of both the long and short-run models was selected based on the Akaike Info Criteria (AIC).

4.2 Presentation of Long-run ARDL Model Results

The result of the estimated long-run result of the relationship between dependent and independent variables in Nigeria is presented in Table 5 below:

Table 5: Long-run ARDL Model Results

Long Run Coefficients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
EG	-6.4E-05	0.000254	-0.2516	0.8041
L(POP)	-0.09705	0.008041	-12.069	0
OPEN	0.000352	0.000142	2.488926	0.0223
L(DT)	0.007602	0.003283	2.31539	0.0319
C	5.782208	0.121488	47.59477	0

Source: Authors' computation, 2024

The provided table presents the estimated long-run coefficients from an econometric model, along with their associated standard errors, t-statistics, and probability values. These results offer insights into the long-run effect of the independent variables.

The coefficient for the variable EG (economic growth) is -0.000064, which

suggests that in the long run, a one-unit increase in economic growth is associated with an approximate 0.0064% decrease in human capital development, holding all other variables constant. However, this effect is not statistically significant, as the corresponding p-value of 0.8041 is well above the conventional significance level of 0.05, indicating that we cannot reject the null hypothesis of no effect. The coefficient for the variable LPOP (population) is -0.09705, which implies that a one-unit increase in population is associated with a negligible decrease in the dependent variable in the long run. The effect is highly significant, with a p-value of 0.0000, strongly indicating that the null hypothesis can be confidently rejected. This suggests that there is statistical evidence to support the existence of a meaningful effect.

In contrast, the coefficient for LDT (digital technology) is 0.007602, suggesting that a one-unit increase in digital technology corresponds to a 0.76% rise in human capital development over the long term. Moreover, this effect is statistical significance, as indicated by a p-value of 0.0319. Also, the coefficient for the variable LOPEN (trade openness) is 0.000352, suggesting that a one-unit increase in trade openness is associated with a 0.035% increase in human capital development in the long run. Similar to the previous variables, this impact is statistically significant, with a p-value of 0.0223.

The constant term, 5.782208, represents the estimated value of the dependent variable when all other variables in the model are held at zero. This value is statistically significant, as the p-value of 0.0000 indicates that we can reject the null hypothesis that the constant is equal to zero.

4.3 Presentation of Short-run ARDL Model Results

The result of the estimated short-run dynamics of the relationship between dependent and independent variables in Nigeria is presented in Table 6:

Table 6: Error Correction Representation for the Selected ARDL (3,0,0,0,4)
Selected based on the AIC Criterion, the Dependent Variable is D(HDC)

Cointegrating Form				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(HCD(-1))	1.100824	0.16445	6.693968	0.0000
DLOG(HCD(-2))	0.11665	0.164797	0.707842	0.4876
DLOG(HCD(-3))	0.331549	0.167399	1.980595	0.0623

D(EG)	-7.5E-05	0.000298	-0.25069	0.8047
DLOG(POP)	-0.11344	0.01932	-5.87147	0.0000
D(OPEN)	0.000412	0.000164	2.504471	0.0215
DLOG(DT)	0.005992	0.007779	0.77026	0.4506
DLOG(DT(-1))	-0.04304	0.011976	-3.59343	0.0019
DLOG(DT(-2))	0.007351	0.01087	0.67632	0.5070
DLOG(DT(-3))	0.036742	0.009803	3.748123	0.0014
CointEq(-1)	-1.16892	0.145137	-8.05388	0.0000
Cointeq = LOG(HCD) - (-0.0001*EG -0.0970*LOG(POP) + 0.0004*OPEN + 0.0076*LOG(DT) + 5.7822)				

Source: Authors' computation, 2024

The table 6 presented the estimated coefficients for the cointegrating form, representing the short-term dynamics and adjustment process toward the long-run equilibrium. This analysis is typically conducted within the framework of a cointegration model, where variables are assumed to be non-stationary but have a long-run equilibrium relationship.

The coefficient for the first lagged dependent variable, D(HCD(-1)), is 1.100824, which suggests that a one-unit increase in the previous period's change in the dependent variable is associated with a 1.100824-unit increase in the current period's change in the dependent variable, holding all other variables constant. This effect is statistically significant, as indicated by the p-value of 0.0000, which is well below the conventional significance level of 0.05. The other two lags of D(HCD) are not statistically significant.

The coefficient for D(EG), which captures the change in economic growth, stands at -0.000075. This suggests that a one-unit increase in economic growth is linked to a -0.000075 unit decrease in the change of the dependent variable, assuming all other factors remain constant. However, this effect is not statistically significant, with a p-value of 0.804. On the other hand, D (LPOP), which represents the change in population, shows a coefficient of -0.11344. This signifies that a 1% increase in population is associated with a reduction in human capital development of approximately 0.097%, ceteris paribus, effectively a negligible decrease. Nonetheless, this effect is statistically significant, with a p-value of 0.0000, providing sufficient evidence to reject the null hypothesis and suggesting a

genuine effect. Also, trade openness exerts a positive and significant effect on human capital. With a coefficient of 0.0004, though quantitatively small, influence on human capital development.

Furthermore, the results also show that changes in digital technology (DL(DT)) influence human capital across different time periods. The current change (DL(DT)) displays a minimal but non-significant effect but future adjustments (DL(DT(-1)) and DL(DT(-3)) exhibit stronger effects. The analysis shows that the first change in digital technology (DL(DT(-1))) produces a negative result which implies immediate changes after digital technology adoption often lead to temporary operational difficulties, the second lag shows no significance while the third lag measurement (DL(DT(-3))) reveals a statistically significant positive effect. The initial negative effect may be due to the adjustment costs incurred during technology adaptation and the time lag needed to learn new digital systems. Users, including students, educators, and educational institutions, need time to learn the new digital platforms and educational systems after making investments in digital infrastructure. The adaptation period causes productivity to decrease as people learn to use new technologies. These results also establish that initial negative consequences from digital technology implementations will be compensated by longer-lasting positive impacts of technological innovation over time.

The error correction model features a positive and statistically significant coefficient value of − 1.16892 for its cointegrating residual (CointEq) in the previous time period. with high statistical significance (t-statistic = − 8.05, p =0.0000). The negative and statistically significant value of the adjustment coefficient indicates that the variables demonstrate a long-term cointegrating connection. The adjustment speed is fast because the absolute value of its magnitude exceeds one. The process therefore responds rapidly to decrease the error by 116.9 percent between periods. An adjustment response rate reaching 116.9% suggests that the mechanism reacts intensely and might generate an oscillatory path toward equilibrium following a shock.

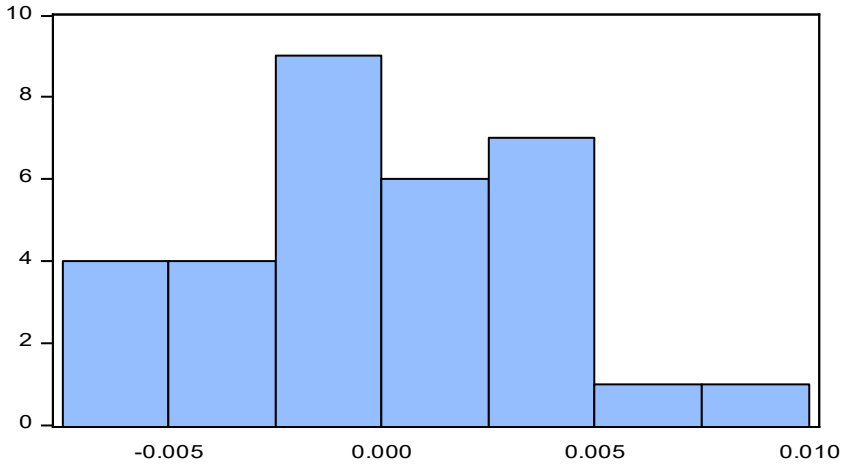


Figure 2: The normality test.

Source: Author's computation, 2024

The result of the normality test is shown in Figure 2. The result shows that the residual is normally distributed with a probability value greater than 0.05(five percent) which marks the acceptance of the null hypothesis.

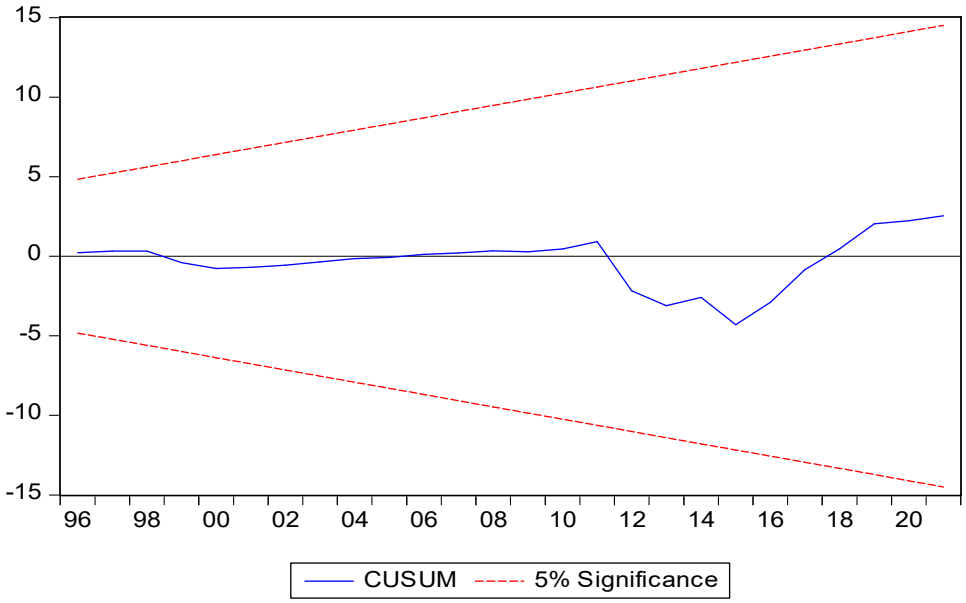


Figure 3: Stability test result (CUSUM)
Source: Author's computation, 2024

The result of the stability test is shown in the figure 3. Since the blue line falls between the two red lines (above and below), it implies that the residual is stable. Therefore, from the foregoing, using the recursive estimate test, we conclude that the residual is stable since the blue line falls between the two red lines.

Discussion of the results

The research demonstrates a positive statistical effect of digital technology infrastructure on human capital growth in Nigeria. Although it confirms certain earlier results, it provides distinct findings in essential areas. The result is similar to Chen et al. (2023), who reveal that digital infrastructure strengthens operational efficiency and financial performance in Chinese firms. In addition, the result is also similar to Barasa (2021), who proves how digital investments created successful results for enhancing digital literacy and innovation in Kenya and Rwanda. The result can also be compared to Wang and Si (2024), who observed that libraries successfully bridge digital divides by conducting digital literacy training according to their assessment of the digital divide in Nigeria. However, the current research extends previous research about institutional and firm-level benefits to measure national impacts on human capital development.

The findings also show that while digital infrastructure creates enduring advantages in the long run, it produces temporary disturbances initially. This is in tandem with the study of Eke (2023), who pointed out that Nigeria faces major barriers in adopting digital technology due to unreliable power supply and weak internet connection. Similarly, the human development index in Nigeria has faced limited improvements from fintech innovations such as ATMs and mobile banking because these services have low penetration in rural regions, according to Origin et al. (2024). This means that the initial negative effect of Digital technology exhibited by the finding is because of systemic problems that organisations must resolve before achieving long-term positive outcomes.

5. Conclusion and Recommendation

Based on the above and the findings, the study concluded that digital technology infrastructure exert a statistically significant positive long-term effect on human capital development in Nigeria within the study period. The study reveals three main obstacles to digital transformation consisting of short-term disruptions and insufficient infrastructure and population growth that overburdens education and technological resources. The study demonstrates trade openness as supportive for human capital development, but population growth shows negative implications, which may prevent digital transformation from reaching its full potential unless comprehensive policy interventions are implemented. The study, therefore, recommends that the government

should prioritise the expansion of the broadband infrastructure development especially in rural and underserved areas. This can be achieved through public-private partnership that provides incentives to telecom providers in order to extend network to remote area. In addition, the government should reduce the cost of internet services through regulatory support and infrastructure subsidies to ensure wider access to digital learning and development of a more skilled workforce in Nigeria.

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