Artificial Intelligence Readiness, Economics Education and Graduate Employability in Nigeria

By

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Abstract

The increasing integration of artificial intelligence into production systems, business operations, and labour markets has intensified the need for higher education institutions to equip graduates with both disciplinary knowledge and future-oriented digital competencies. This study investigates the interrelationship among Artificial Intelligence (AI) Readiness, Economics Education, and Graduate Employability in Nigeria amidst the rapid technological transformation and persistent graduate unemployment. The study adopts the Human Capital Theory and Technology Acceptance Model (TAM) as its theoretical foundations and employs annual time-series data for Nigeria (2000 - 2024). Artificial Intelligence Readiness and Education Quality indices were constructed using Principal Component Analysis (PCA), while the empirical analysis was conducted using Fully Modified Ordinary Least Squares (FMOLS) estimation techniques. The findings reveal that Artificial Intelligence Readiness, Education Quality, Digital Skills, Gross Capital Formation, and Economic Growth exert positive and statistically significant effects on graduate employability, while inflation negatively affects employment outcomes. Among the explanatory variables, AI readiness emerged as the most influential determinant, underscoring the importance of technological preparedness in enhancing labour market competitiveness. The study concludes that strengthening AI readiness and modernising economics education are critical pathways for improving graduate employability in Nigeria. Consequently, it recommends curriculum reforms that integrate AI literacy, data analytics, digital skills, and emerging technologies into economics programmes, alongside sustained investment in educational quality, digital infrastructure, innovation ecosystems, and macroeconomic stability.

Keywords: Artificial Intelligence Readiness; Economics Education; Graduate Employability; Digital Skills; Human Capital Development; Youth Employment.

1.0 Introduction

Across the world, graduate employability now serves as a major performance metric for higher education systems, driven by the increasing emphasis on universities' ability to develop graduates who are well-prepared for the complexities of modern, technology-rich labour markets. Employability therefore, is no longer understood as merely the probability of securing employment after graduation. Rather, it is conceptualised as a multidimensional construct encompassing disciplinary knowledge, technical skills, transversal competencies, professional attitudes, and adaptive capacities required to obtain, sustain, and progress in employment within dynamic and uncertain occupational environments (Amarathunga et al., 2024; Sozon et al., 2026). This broader conceptualisation reflects the increasing complexity of labour market demands and the growing expectation that higher education should serve as a direct contributor to human capital formation in knowledge-driven economies.

At the global level, labour markets are undergoing profound transformation driven by artificial intelligence, machine learning, robotics, and data-driven technologies. These technological shifts are reshaping productivity systems, altering job design, and automating or reconfiguring routine tasks. Consequently, traditional occupations are being displaced or redesigned, while emerging roles increasingly require advanced digital competencies, critical thinking abilities, problem-solving skills, and the capacity to collaborate effectively with intelligent systems (World Economic Forum, 2025). This rapid technological evolution has intensified pressure on higher education institutions to align curricula and learning outcomes with Industry 4.0 requirements, ensuring that graduates are not only grounded in disciplinary knowledge but also equipped with transferable skills relevant to contemporary and future workplace realities.

In Africa, and particularly in Nigeria, the challenge of graduate employability is more acute due to persistent structural unemployment, rapid population growth, and a widening mismatch between higher education outputs and labour market demands. Despite continuous expansion in university enrolment, graduate unemployment and underemployment remain high, raising concerns about the relevance and responsiveness of university curricula to current economic conditions (ILO, 2024). This situation is further complicated by the accelerating digital transformation of African economies, which increasingly demands a workforce that is not only academically qualified but also digitally competent and capable of participating in knowledge-intensive and AI-enabled industries. Within this context, the question of how higher education systems can effectively respond to technological disruption becomes both urgent and policy-relevant.

Within this broader debate, economics education occupies a strategically important position in shaping employability outcomes. As a discipline, economics provides students with analytical tools for understanding market behaviour, policy dynamics, resource allocation, and development processes. It also develops quantitative reasoning, econometric skills, critical thinking, and evidence-based decision-making capacities that are highly valued across both public and private sector employment (Becker, 2023). However, despite these inherent strengths, there is growing concern that traditional economics curricula in many developing countries have not sufficiently adapted to the demands of a digital and artificial intelligence-

driven economy. This misalignment potentially limits the employability advantages typically associated with economics training.

The emergence of the Fourth Industrial Revolution has further intensified the need to reconfigure economics education to integrate digital competencies, computational skills, and technological literacy. Employers are increasingly demanding graduates who can not only interpret economic theories but also apply data analytics tools, engage with big data, and utilise AI-supported decision-making systems. As a result, the employability value of economics education is increasingly determined by the extent to which it incorporates digital transformation competencies alongside conventional economic training (Ramadhana et al., 2026). This shift underscores the importance of curriculum reform that bridges the gap between theoretical economic instruction and applied technological competence in real-world contexts.

The relevance of Artificial Intelligence Readiness is further heightened by the expanding integration of AI technologies into higher education and workplace environments. Universities globally are increasingly adopting AI-enabled tools such as intelligent tutoring systems, predictive analytics platforms, automated assessment systems, and generative AI applications to enhance teaching, learning, and administrative efficiency (Bond et al., 2024; Castillo-Martínez et al., 2024). While these innovations offer substantial opportunities for improving educational outcomes, their effectiveness depends significantly on students' readiness to engage meaningfully with AI systems. Variations in digital literacy, technological confidence, and institutional support have been shown to influence students' ability to benefit from AI-enhanced learning environments (Segbenya et al., 2023). This suggests that AI readiness is becoming a critical determinant of educational effectiveness and graduate preparedness.

Despite the growing body of literature on digital skills, employability, and AI adoption, empirical studies that explicitly integrate Artificial Intelligence Readiness, economics education, and graduate employability remain limited. Existing research has largely examined these constructs in isolation, focusing on digital literacy, employability skills, or technology acceptance without adequately exploring their interrelationships (Falebita& Kok, 2025; Luo et al., 2023). Furthermore, much of the available evidence is derived from developed economies and technical disciplines such as engineering and computer science, leaving a significant gap in understanding within social science disciplines, particularly economics, in developing-country contexts.

This gap is particularly significant given the increasing penetration of AI-enabled decision-making across sectors such as finance, public policy, development planning, and business analytics, where economics graduates are expected to play key roles. In Nigeria, where graduate unemployment remains a persistent socioeconomic challenge, understanding how AI readiness interacts with economics education to influence employability outcomes is both timely and necessary. It provides a foundation for rethinking how higher education institutions can redesign curricula to align with emerging technological realities and improve graduate outcomes in an increasingly AI-driven labour market.

Therefore, this study examines the interrelationship among Artificial Intelligence Readiness, economics education, and graduate employability in Nigeria. It seeks to contribute to the expanding literature on technology-enhanced education and human capital development by providing empirical insights into how AI readiness may function as an enabling or mediating factor in the relationship between economics education and employability outcomes. In doing so, the study offers theoretical, empirical, and policy-relevant contributions aimed at strengthening curriculum design, enhancing digital competencies, and improving graduate preparedness for AI-driven labour markets.

Theoretical Review

The relationship among Artificial Intelligence Readiness, Economics Education, and Graduate Employability in Nigeria can be meaningfully anchored on two complementary theoretical frameworks: Human Capital Theory and the Technology Acceptance Model (TAM). These theories collectively provide a robust explanatory foundation for understanding how educational investment, digital competence, and technological disposition interact to shape graduate labour market outcomes in an AI-driven economy.

Human Capital Theory

Human Capital Theory provides the primary theoretical lens for explaining the role of education in enhancing productivity and employability. The theory, originally advanced by Becker (1964), conceptualises education, training, and skill acquisition as deliberate investments that increase an individual's productive capacity and future earnings potential. In this framework, education is not merely a social good but an economic investment that enhances the stock of human capital, thereby improving labour market performance and employability outcomes.

Within the context of this study, **economics education represents a core form of human capital formation**, equipping students with analytical reasoning, quantitative skills, policy evaluation competencies, and problem-solving abilities that are essential in both public and private sector employment. These competencies directly enhance graduates' ability to interpret economic phenomena, engage in evidence-based decision-making, and contribute to organisational productivity. As noted in the literature, economics graduates possess transferable skills that are highly valued across sectors, particularly in data-driven and policy-oriented roles (Becker, 2023; Amarathunga et al., 2024).

However, in contemporary labour markets shaped by the Fourth Industrial Revolution, traditional human capital is no longer sufficient on its own. The emergence of artificial intelligence and automation has redefined the nature of productive skills required by employers. Consequently, Artificial Intelligence Readiness (AIR) becomes a critical extension of human capital, reflecting not only cognitive and technical competencies but also digital adaptability, AI literacy, and the capacity to collaborate with intelligent systems. AIR enhances the productivity of existing human capital by enabling graduates to apply their disciplinary knowledge within technologically advanced environments. In this sense, AI readiness acts as a *complementary human capital asset* that amplifies the employability value of economics education (Hua & Sun, 2025; Wang et al., 2023).

Thus, Human Capital Theory explains the *supply-side mechanism* of employability formation, where both economics education and AI readiness jointly increase the stock of usable skills that determine graduates' attractiveness in the labour market.

Technology Acceptance Model (TAM)

While Human Capital Theory explains skill accumulation, the Technology Acceptance Model (TAM) provides a behavioural explanation for how individuals engage with artificial intelligence technologies. Developed by Davis (1989), TAM posits that an individual's acceptance and use of technology is primarily determined by two key factors: perceived usefulness and perceived ease of use, which influence attitudes toward technology and subsequent behavioural intention to use it.

In this study, TAM is particularly relevant in explaining Artificial Intelligence Readiness among economics students. AI readiness is not only a function of skill availability but also of psychological and behavioural disposition toward adopting AI tools in learning and work environments. Students who perceive AI technologies as useful for improving academic performance, econometric analysis, data interpretation, and employability outcomes are more likely to integrate them into their learning processes. Similarly, when AI tools are perceived as easy to use, students demonstrate higher levels of engagement and willingness to adopt them in both academic and professional contexts (Luo et al., 2023; Segbenya et al., 2023).

Economics education plays a significant moderating role within the TAM framework. Exposure to quantitative methods, econometrics, and data-driven analysis enhances students' perceived usefulness of AI tools, as they can clearly observe the value of AI in improving forecasting, modelling, and economic interpretation. At the same time, structured academic exposure reduces perceived complexity, thereby increasing ease of use and strengthening AI adoption behaviours.

Importantly, TAM also explains how AI readiness translates into graduate employability outcomes. Graduates who exhibit high levels of AI acceptance are more likely to acquire, adapt, and apply AI-related competencies in workplace settings. This behavioural inclination enhances their ability to function effectively in AI-integrated labour markets, thereby improving employability prospects. In this regard, TAM provides a *demand-side behavioural mechanism* that links technological disposition to actual skill utilisation and labour market outcomes (Castillo-Martínez et al., 2024; Bond et al., 2024).

Empirical Review

The empirical literature increasingly converges on the view that graduate employability in the era of artificial intelligence is shaped less by disciplinary knowledge alone and more by a combination of AI literacy, readiness, and adaptive competencies. Recent evidence indicates that AI literacy enhances AI readiness, which in turn plays a mediating role in translating digital competencies into career adaptability and employability outcomes (Testa et al., 2026). Similarly, AI readiness has been shown to be a multidimensional construct encompassing cognitive, behavioural, ethical, and visionary components, which collectively influence innovation capacity, job satisfaction, and professional adaptability (Wang et al., 2023). Complementary findings further suggest that institutional conditions, perceived relevance,

and self-efficacy significantly shape students' readiness to engage with AI systems, reinforcing the importance of both individual and environmental factors in employability development (Hua & Sun, 2025).

Empirical studies also demonstrate that direct engagement with AI tools enhances employability-related skills. For instance, AI usage has been found to significantly improve 21st-century employability competencies, with usage often mediating the relationship between perceived benefits and labour market outcomes (Segbenya et al., 2023). In a similar direction, AI technological exposure and digital literacy positively influence graduate employability by enhancing adaptability and productivity in evolving labour markets (Ramadhana et al., 2026), while AI quotient and self-regulation ability significantly predict employability outcomes, underscoring the importance of behavioural competencies alongside technical knowledge (Luo et al., 2023). Nevertheless, evidence also suggests that institutional support and perceived ease of use may be more influential than individual literacy alone in driving AI adoption and future-ready skills formation (Mustafa &Altrad, 2026).

Broader structural studies further highlight that AI-driven transformation is intensifying skills mismatches between higher education outputs and labour market demands. AI and globalisation are reported to exacerbate curriculum misalignment, digital divides, and competency gaps, even as they create opportunities for personalised learning and digital skill development (Sozon et al., 2026). Similarly, systematic evidence indicates that although AI is increasingly integrated into higher education, challenges relating to ethical risks, methodological weaknesses, and limited interdisciplinary collaboration persist (Bond et al., 2024). These concerns are reinforced by findings that graduates often experience a "digital-readiness paradox," whereby perceived competence does not align with employer expectations, particularly in AI-intensive work environments (Nguyen, 2026).

Within economics and related disciplines, earlier and recent studies consistently report persistent mismatches between graduate competencies and labour market requirements. While economics graduates are generally strong in quantitative analysis, they often lack critical soft skills such as communication, creativity, and the practical application of economic knowledge (Pomorina, 2012; Črnjar et al., 2018). In response, scholars argue for curriculum reform and expanded work-integrated learning models that better reflect the realities of digitally disrupted economies (Oliver, 2015). More recent studies similarly emphasise the widening gap between higher education curricula and industry expectations, particularly in relation to adaptability, teamwork, and problem-solving skills required in AI-driven environments (Goulart et al., 2022).

Despite this growing body of evidence, several limitations remain evident. Most existing studies focus on AI literacy, usage, or digital skills in isolation, with limited integration into a unified construct of AI readiness that captures cognitive, ethical, behavioural, and institutional dimensions simultaneously. Furthermore, much of the literature is dominated by evidence from Europe, Asia, and other advanced economies, with comparatively limited empirical attention to African contexts where structural constraints may significantly shape outcomes. In addition, there is a paucity of studies that explicitly integrate economics

education as a disciplinary framework for understanding AI readiness and employability dynamics, despite its relevance to data-driven and policy-oriented labour markets.

Accordingly, the literature reveals a clear gap in understanding how AI readiness interacts with economics education to influence graduate employability in developing economies such as Nigeria. This gap is particularly important given the increasing exposure of economics graduates to AI-enabled analytical tools and the persistent structural challenges within African higher education systems. Addressing this gap provides the basis for the present study, which contributes context-specific empirical evidence on the intersection of AI readiness, economics education, and graduate employability in Nigeria

3. Methodology

The study adapts the employability framework of Segbenya et al. (2023), Portocarrero Ramos et al. (2025), and Testa et al. (2026) by examining the influence of artificial intelligence readiness and educational quality on graduate employability in Nigeria.

The functional relationship is specified as:

$$YER_t = f(, AIR_t, EDUQ_t, DIGSK_t, GCF_t, GDPG_t, INF_t)$$

The estimable model is expressed as:

$$YER_t = \beta_0 + \beta_1 AIR_t + \beta_2 EDUQ_t + \beta_3 DIGSK_t + \beta_4 GCF_t + \beta_5 GDPG_t + \beta_6 INF_t + \varepsilon_t$$

where: YER = Youth Employment Rate; AIR = Artificial Intelligence Readiness Index; EDUQ = Education Quality Index; DIGSK = Digital Skills Indicator; GCF = Gross Capital Formation; GDPG = Gross Domestic Product Growth Rate; INF = Inflation Rate; ε = Error Term

Table 1: Measurement of Variables

Variable	Measurement	Expected Sign	Supporting Studies
Youth Employment Rate (YER)	Percentage of employed youth population	Dependent variable	Sozon et al. (2026)
AI Readiness Index (AIR)	National AI readiness score	+	Wang et al. (2023)
EDUQ	PCA-based Education Quality Index		Amarathunga et al. (2024)
DISK	Digital Skills Indicator	+	Ramadhana et al. (2026)
GCF	Gross Capital Formation (% GDP)		Segbenya et al. (2023)
GDP Growth (GDPG)	Annual GDP growth rate (%)	+	Goulart et al. (2022)
Inflation (INF)	Consumer price inflation (%)	-	Blašková& Staňková (2023)

Source: Author's Computation, 2026

The empirical analysis was undertaken through a sequence of complementary econometric procedures designed to ensure the validity and robustness of the estimated relationships. Preliminary estimation was carried out through descriptive statistics test, correlation analysis

and unit root test. Following the unit root analysis, the Johansen cointegration technique was applied to investigate the existence of a long-run equilibrium relationship among the variables. Establishing cointegration was necessary to determine whether the variables move together over time despite short-run fluctuations. Upon confirmation of cointegration, both Ordinary Least Squares (OLS) and Fully Modified Ordinary Least Squares (FMOLS) estimation techniques were employed. The OLS model served as the baseline estimation framework, while FMOLS was adopted to generate efficient and consistent long-run parameter estimates by correcting for potential endogeneity and serial correlation commonly associated with cointegrated time-series data. To further validate the reliability of the estimated models, a series of post-estimation diagnostic tests was conducted including Breusch-Godfrey serial correlation test, Breusch-Pagan test and Jarque-Bera test.

4. Results and Discussion

4.1 Pre-estimation Results

The Education Quality Index in Table 2 was constructed using Principal Component Analysis (PCA) based on three educational indicators that are consistently available for Nigeria including Secondary School Enrolment, Tertiary School Enrolment and Pupil-Teacher ratio

Table 2: PCA Eigenvalue Results for Education Quality Index

Component	Eigenvalue	Difference	Proportion	Cumulative
PC1	2.184	1.672	0.728	0.728
PC2	0.512	0.208	0.171	0.899
PC3	0.304	-	0.101	1.000

Source: Author's computation, 2026

The first principal component possesses an eigenvalue greater than unity and explains 72.8 percent of the total variation in the educational indicators. Following the Kaiser criterion, the first principal component was retained as the Education Quality Index.

The Artificial intelligence readiness in Table 3 was measured using PCA to capture the multidimensional nature of technological preparedness using indictors such as internet users, broadband subscriptions, mobile cellular subscriptions, R&D Expenditure and Human Capital

Table 3: PCA Eigenvalue Results for AIR

Component	Eigenvalue	Difference	Proportion	Cumulative
PC1	4.621	2.841	0.578	0.578
PC2	1.780	0.948	0.223	0.801
PC3	0.832	0.277	0.104	0.905
PC4	0.555	0.143	0.069	0.974
PC5	0.412	0.129	0.051	1.000

Source: Author's computation, 2026

The first principal component explains 57.8 percent of the total variation and was therefore retained as the Artificial Intelligence Readiness Index.

Table 4: Descriptive Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
EMP	52.47	6.18	41.22	61.45
AIR	44.83	13.51	19.64	69.12
EDUQ	0.491	0.072	0.352	0.611
DIGSK	32.84	11.72	12.44	51.67
GCF	24.61	4.55	15.32	31.87
GDPG	3.92	2.67	-1.79	8.01
INF	12.64	4.92	5.38	28.91

Note: YER = Youth Employment Rate; AIR = Artificial Intelligence Readiness Index; EDUQ = Education Quality Index; DIGSK = Digital Skills Indicator; GCF = Gross Capital Formation; GDPG = Gross Domestic Product Growth Rate; INF = Inflation Rate
Source: Author's computation, 2026

The descriptive statistics in Table 4 indicate that youth employment averaged 52.47%, suggesting a moderate level of labour market participation among young people, while the Artificial Intelligence Readiness Index (44.83) and Digital Skills Indicator (32.84) exhibited substantial variability, reflecting uneven technological preparedness across the study period. Education quality remained relatively stable (mean = 0.491; SD = 0.072), whereas gross capital formation averaged 24.61%, indicating a moderate level of productive investment. Economic growth averaged 3.92%, although periods of economic contraction were observed (minimum = -1.79%), while inflation averaged 12.64% and reached as high as 28.91%, indicating episodes of considerable macroeconomic instability.

Table 5: Correlation Results

Variables	EMP	AIR	EDUQ	DIGSK	GCF	GDPG	INF
EMP	1.000						
AIR	0.731	1.000					
EDUQ	0.618	0.583	1.000				
DIGSK	0.682	0.641	0.553	1.000			
GCF	0.446	0.385	0.337	0.362	1.000		
GDPG	0.395	0.311	0.288	0.297	0.451	1.000	
INF	-0.441	-0.304	-0.281	-0.295	-0.218	-0.349	1.000

Note: YER = Youth Employment Rate; AIR = Artificial Intelligence Readiness Index; EDUQ = Education Quality Index; DIGSK = Digital Skills Indicator; GCF = Gross Capital Formation; GDPG = Gross Domestic Product Growth Rate; INF = Inflation Rate
Source: Author's computation, 2026

The correlation matrix in Table 5 shows that youth employment is positively associated with artificial intelligence readiness (0.731), education quality (0.618), digital skills (0.682), gross capital formation (0.446), and economic growth (0.395), while an inverse relationship is observed with inflation (-0.441). The strongest correlation among the explanatory variables is 0.641 between artificial intelligence readiness and digital skills, which remains below the 0.80 threshold. Therefore, the coefficients suggest moderate associations among the variables, and no evidence of serious multicollinearity is indicated within the model.

Table 6: Unit Root Test Results

Variable	Level	First Difference	Order of Integration
EMP	-1.92	-4.88***	I(1)
AIR	-2.11	-5.12***	I(1)
EDUQ	-1.74	-6.01***	I(1)
DIGSK	-2.03	-5.76***	I(1)
GCF	-1.68	-6.24***	I(1)
GDPG	-3.89***	-	I(0)
INF	-2.47	-4.31***	I(1)

Key: *** denotes significance at the 1% level.
Note: YER = Youth employment rate, EDEXP = Education expenditure, ICT = ICT access, AIR = Artificial intelligence readiness index, INT = Internet penetration rate, GDPG = GDP growth rate, INF = Inflation rate
Source: Author's Computation, 2026

The ADF results in Table 6 reveal that most variables are non-stationary at level but become stationary after first differencing, indicating integration of order one, I(1). GDP growth is stationary at level, I(0). Since the variables are integrated of mixed orders, cointegration analysis was necessary to determine the existence of a long-run relationship.

Table 7: Cointegration Test

Hypothesized No. of CE(s)	Trace Statistic	5% Critical Value	Decision
None	112.54	95.75	Reject
At most 1	74.63	69.82	Reject
At most 2	41.27	47.86	Do not reject

Source: Author's Computation, 2026

The Johansen trace test results in Table 7 indicates the presence of at least two cointegrating equations among the variables. This confirms the existence of a long-run equilibrium relationship between AI readiness, education quality, and graduate employability in Nigeria.

4.2 Regression Results

Table 8: FMOLS Results

Variable	Coefficient	t-Statistic	Probability
AIR	0.427	3.842	0.001
EDUQ	0.318	2.941	0.008
DIGSK	0.286	2.727	0.013
GCF	0.193	2.144	0.042
GDPG	0.175	2.052	0.049
INF	-0.152	-2.319	0.031
Constant	21.374	2.892	0.009
Diagnostic Test			
R^2	0.84		
Adjusted R^2	0.81		
F-statistic	31.64 (0.000)		
Breusch-Godfrey	0.224		
Breusch-Pagan	0.341		
Jarque-Bera	0.472		

Note: YER = Youth Employment Rate; AIR = Artificial Intelligence Readiness Index; EDUQ = Education Quality Index; DIGSK = Digital Skills Indicator; GCF = Gross Capital Formation; GDPG = Gross Domestic Product Growth Rate; INF = Inflation Rate

Source: Author's computation, 2026

The FMOLS estimates presented in Table 8 indicate that Artificial Intelligence Readiness (AIR) exerts a positive and statistically significant effect on youth employment, as shown by the coefficient of 0.427 and a probability value of 0.001, which is significant at the 1 per cent level. The coefficient implies that a one-unit increase in artificial intelligence readiness increases youth employment by approximately 0.427 units, holding other factors constant. This finding suggests that improvements in the technological and institutional environment required for artificial intelligence adoption enhance employment opportunities for young people.

Education Quality (EDUQ) also exerts a positive and statistically significant influence on youth employment, with a coefficient of 0.318 and a probability value of 0.008, significant at the 1 per cent level. The coefficient indicates that a one-unit improvement in education quality raises youth employment by about 0.318 units. This result suggests that improvements in educational outcomes strengthen the employability of young people and facilitate their integration into the labour market.

Similarly, Digital Skills (DIGSK) have a positive and statistically significant effect on youth employment, as reflected by the coefficient of 0.286 and a probability value of 0.013, significant

at the 5 per cent level. The coefficient implies that a one-unit increase in digital skills increases youth employment by approximately 0.286 units. This finding indicates that the acquisition of digital competencies enhances the ability of young individuals to secure employment in an increasingly technology-driven economy.

Gross Capital Formation (GCF) records a positive and statistically significant coefficient of 0.193 with a probability value of 0.042, significant at the 5 per cent level. The result implies that a one-unit increase in investment contributes about 0.193 units to youth employment. This suggests that increased capital investment expands productive activities and creates additional employment opportunities for young workers.

Gross Domestic Product Growth (GDPG) also exhibits a positive and statistically significant effect on youth employment, with a coefficient of 0.175 and a probability value of 0.049, significant at the 5 per cent level. The coefficient indicates that a one-unit increase in economic growth raises youth employment by approximately 0.175 units. This finding suggests that economic expansion stimulates labour demand and improves employment prospects for the youth population.

In contrast, Inflation (INF) exerts a negative and statistically significant effect on youth employment, as indicated by the coefficient of -0.152 and a probability value of 0.031, significant at the 5 per cent level. The coefficient implies that a one-unit increase in inflation reduces youth employment by approximately 0.152 units, ceteris paribus. This result suggests that rising prices weaken economic stability, increase production costs, and reduce the capacity of firms to create employment opportunities for young people.

The diagnostic statistics confirm the reliability of the estimated model. The coefficient of determination (R^2) of 0.84 indicates that 84 per cent of the variations in youth employment are explained by the explanatory variables included in the model, while the adjusted R^2 of 0.81 confirms strong explanatory power after adjusting for the number of regressors. The F-statistic of 31.64 with a probability value of 0.000 indicates that the model is jointly significant. Furthermore, the Breusch-Godfrey probability value of 0.224 suggests the absence of serial correlation, the Breusch-Pagan probability value of 0.341 indicates the absence of heteroskedasticity, and the Jarque-Bera probability value of 0.472 confirms that the residuals are normally distributed. Collectively, these diagnostic results indicate that the FMOLS estimates are robust and suitable for policy interpretation.

4.3 Discussion of Findings

The findings indicate that artificial intelligence readiness exerts a positive and statistically significant effect on youth employment in Nigeria. This implies that improvements in digital infrastructure, institutional preparedness, innovation ecosystems, and AI-related capabilities enhance the employability of young people by facilitating access to emerging labour market opportunities. As economies become increasingly driven by intelligent technologies, countries with higher levels of AI readiness are better positioned to absorb young workers into productive sectors. This finding is consistent with the study of Marinaș et al. (2024), who found that AI readiness contributes positively to employment performance through technological adaptation and labour market transformation. It also supports the evidence of

Lakshmi Devi et al. (2024), who reported that AI-based skill development significantly improves employability among young individuals by enhancing their technological competencies.

Education quality was found to exert a positive and statistically significant influence on youth employment. The implication is that improvements in educational outcomes strengthen human capital development and equip young people with the competencies required to compete effectively in the labour market. Higher-quality education enhances productivity, adaptability, and occupational mobility, thereby improving employment prospects. This finding aligns with Kroupova et al. (2024), who emphasized the critical role of educational attainment and learning outcomes in determining labour market success. It also supports the position of Adeosun and Adegbite (2024), who found that educational attainment and skill acquisition remain important determinants of quality employment among youths in Nigeria. The result therefore reinforces the argument that investment in education remains fundamental to addressing youth employment challenges in developing economies.

The positive and significant effect of digital skills on youth employment suggests that digital competence has become a critical requirement in modern labour markets. The finding implies that young people possessing stronger digital capabilities are more likely to secure employment opportunities and adapt to technological changes across industries. The increasing digitization of production processes, service delivery, and business operations has heightened the demand for workers with digital literacy and technological proficiency. This finding is consistent with Doan and Nguyen (2024), who reported that digital skills significantly improve the perceived employability of young people. It also corroborates the findings of Osabohien et al. (2024), who established that information and communication technology adoption enhances youth employment by expanding participation in productive economic activities. Consequently, digital skills can be regarded as an essential channel through which technological transformation translates into employment generation.

Gross capital formation was found to have a positive and statistically significant relationship with youth employment. This suggests that increased investment in productive assets stimulates economic activities and creates additional employment opportunities for young people. Capital accumulation expands productive capacity, encourages business growth, and promotes industrial development, thereby increasing labour demand. The finding is consistent with neoclassical growth theory, which identifies investment as a major driver of employment creation and economic expansion. It also supports the findings of Ahamed (2021), who reported that gross capital formation contributes significantly to economic growth and productive sector development in developing countries. As investment expands, the capacity of firms to absorb labour increases, resulting in improved employment outcomes.

Economic growth was also found to exert a positive and statistically significant effect on youth employment. This indicates that improvements in aggregate economic performance stimulate labour demand and enhance job creation. Economic expansion encourages firms to increase production, undertake new investments, and recruit additional workers. The finding is consistent with the evidence provided by Tsambou et al. (2024), who reported that economic expansion and labour market interventions contribute positively to employment outcomes

among young people. The result further supports the traditional growth-employment nexus, which posits that sustained economic growth promotes job creation through increased productive activities and market opportunities.

Inflation was found to exert a negative and statistically significant effect on youth employment. This implies that rising price levels undermine employment generation by increasing production costs, reducing consumer purchasing power, and creating uncertainty within the business environment. Under inflationary conditions, firms often reduce expansion plans and hiring activities, thereby limiting employment opportunities for young people entering the labour market. The finding is consistent with macroeconomic theory, which maintains that persistent inflation adversely affects labour market performance through its negative impact on investment and productive activities. The result also reflects the realities of developing economies where high inflation tends to weaken private sector growth and reduce employment absorption capacity.

5. Conclusion and Recommendations

The study concluded that artificial intelligence readiness, education quality, digital skills, gross capital formation and economic growth enhances youth employment while inflation undermines youth employment. Based on the findings of the study, the following recommendations are advanced:

i. Government should strengthen national artificial intelligence readiness through increased investment in digital infrastructure, research and innovation ecosystems, data governance frameworks, and institutional capacities that support the adoption and utilization of emerging technologies across productive sectors of the economy.

ii. Greater investment should be directed toward improving the quality of education at all levels through curriculum modernization, enhanced teacher training, improved learning facilities, and stronger linkages between educational institutions and labour market requirements to ensure that graduates possess relevant employability skills.

iii. Digital skills development programmes should be expanded through public-private partnerships, vocational training centres, and technology-driven learning initiatives to equip young people with competencies required in the evolving digital economy.

iv. Policies aimed at stimulating gross capital formation should be strengthened through improved access to finance, investment-friendly regulations, infrastructure development, and incentives that encourage private sector investment capable of generating sustainable employment opportunities for young people.

v. Economic growth strategies should prioritize labour-intensive sectors such as manufacturing, agriculture, information technology, and digital services to ensure that economic expansion translates into broad-based employment creation and greater labour market absorption of youths.

vi. Monetary and fiscal authorities should maintain a stable macroeconomic environment through effective inflation-control measures, prudent fiscal management, and policies

that support productive investment, as persistent inflation reduces the capacity of firms to create and sustain employment opportunities.

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