Artificial Intelligence Adoption and Youth Employment Outcomes in Jalingo Metropolis, Taraba State, Nigeria: Opportunities and Challenges

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ABSTRACT

Artificial intelligence (AI) is transforming employment opportunities, productivity and entrepreneurship globally, yet its implications for young people in secondary urban centres of Nigeria remain insufficiently explored. This study examined the relationship between AI adoption and youth employment outcomes in Jalingo Metropolis, Taraba State, Nigeria. A quantitative cross-sectional survey design was adopted, involving 594 respondents aged 18–35 years. Data were collected using a structured questionnaire and analysed using descriptive statistics, binary logistic regression and ordinary least squares regression. The findings revealed that 50.2% of respondents had previously used AI applications, 49.3% reported recent utilisation, while only 20.2% had generated income through AI-supported activities. The reported regression estimates indicated positive associations between AI adoption and employment participation (aOR = 1.567), perceived employability (β = 0.418), earnings among positive earners (+23.5%) and entrepreneurial participation (aOR = 1.596), with reported p-values below .001. However, these statistical estimates require verification against the original regression outputs. Unreliable electricity supply (83.2%), high internet costs (80.3%) and limited access to digital devices (71.2%) emerged as the most frequently reported barriers to AI adoption. Drawing on human capital theory, the Unified Theory of Acceptance and Use of Technology and the automation–augmentation perspective, the study demonstrates that the potential economic benefits of AI depend on digital competencies, infrastructural accessibility and labour-market opportunities. The study recommends practical AI-skills development, improved digital infrastructure and inclusive entrepreneurship support to strengthen youth participation in the digital economy. Given its cross-sectional design, the findings establish associations rather than causal relationships.

Keywords: artificial intelligence; youth; employment; employability; digital skills; entrepreneurship

INTRODUCTION

Artificial intelligence has become a consequential force in contemporary labour markets. Machine learning and generative AI can assist with writing, coding, marketing, information processing and customer communication, enabling individuals and firms to reorganize tasks and sometimes increase productivity. Yet these advances also raise questions about job displacement, changing skill requirements, insecure digital work and uneven access to economic opportunities. Acemoglu and Restrepo (2019) argue that automation displaces labour from existing tasks while innovation may create new tasks that reinstate labour demand. Whether a community gains or loses employment therefore depends not simply on technological diffusion but on the institutions and economic activities surrounding it.

Experimental and organizational evidence has documented meaningful performance gains. Noy and Zhang (2023) found that generative AI improved outcomes on professional writing tasks, while Brynjolfsson et al. (2025) identified productivity improvements among customer-support agents, particularly for less experienced workers. However, evidence of technological substitution is equally important. Hui et al. (2024) documented adverse short-term outcomes for certain categories of freelancers exposed to generative AI. These findings show why individual productivity gains should not automatically be equated with more jobs, better earnings or secure livelihoods.

The Nigerian context intensifies this debate. Labour-market vulnerability extends beyond the conventionally unemployed to people working informally or earning inadequate and unstable incomes. The National Bureau of Statistics (2024) reported substantial informal employment in its second-quarter labour-force survey. AI may help young Nigerians create services, access remote clients or improve small enterprises; it may also accentuate existing differences in education, device ownership, electricity access and internet affordability. Research on global online work further warns that entry into digitally mediated labour need not deliver decent work or equitable bargaining power (Anwar & Graham, 2020; World Bank, 2023).

Jalingo Metropolis is an informative location for investigating these issues outside Nigeria's principal digital-business centres. Its economy encompasses education, public administration, trade and informal services; these sectors may use AI for learning, communication, promotion, administration and enterprise activity. At the same time, local infrastructural constraints may hinder sustained adoption. Usman et al. (2025) discuss youth unemployment in Jalingo, but evidence linking AI use to multiple youth employment outcomes remains sparse. This article addresses that gap by examining adoption, perceived barriers and associations with employment, perceived employability, income and entrepreneurial participation.

Four null hypotheses guide the analysis: H01, AI adoption is unrelated to employment participation; H02, AI adoption is unrelated to perceived employability; H03, AI adoption is unrelated to earnings among positive earners; and H04, AI adoption is unrelated to entrepreneurial participation. The article interprets each association cautiously because cross-sectional survey results cannot by themselves establish causality.

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Artificial Intelligence Adoption and Youth Employment

AI adoption refers to the use of AI-enabled applications for personal, educational, occupational or entrepreneurial activities. In labour-market research, a critical distinction exists between ever having tried an application, routinely using it and obtaining an economic return. Each represents a different degree of engagement. Young people might use AI for learning, job-search assistance or entertainment without finding paying clients or increasing income. Consequently, indicators of adoption should be interpreted alongside indicators of actual economic participation.

Human capital theory treats education, training and accumulated skills as resources that can enhance productivity and labour-market outcomes (Becker, 1993). Applied to AI, the theory suggests that digital proficiency is valuable when it complements substantive occupational knowledge, critical reasoning and communication. Green (2024) notes that AI is changing the composition of skills sought in the labour market. Effective use may require verifying outputs, understanding domain-specific limitations, protecting information and communicating effectively with clients. Familiarity with AI tools alone is insufficient evidence of employability.

For young people facing constraints in experience, finance and networks, AI may lower the costs of entry into certain activities, including content preparation, online promotion, basic business administration and freelance services. Nevertheless, digital labour can be precarious and highly competitive. Anwar and Graham (2020) describe inequalities shaping the position of African workers in the global digital economy. The economic value of AI must therefore be judged by whether it supports sustained and remunerative work rather than merely expanding the number of tasks completed online.

Evidence of Opportunities and Risks

The productivity literature provides reasons for cautious optimism. Noy and Zhang (2023) showed improved speed and quality in writing tasks with generative AI assistance. Brynjolfsson et al. (2025) found that AI support improved customer-service productivity, with particularly notable gains among less experienced agents. At enterprise level, Rajaram and Tinguely (2024) describe opportunities for small and medium enterprises to apply generative AI in organizational processes, while stressing implementation challenges.

Together, these findings suggest that AI can complement labour and improve the efficiency of selected economic activities.

Digital platforms can expand access to customers beyond local boundaries, a potentially important advantage for workers in smaller urban economies. Yet the World Bank (2023) documents both opportunities and risks in online gig work, including concerns about worker protection and earnings uncertainty. Hui et al. (2024) identify reduced short-term demand in some online freelance categories following generative AI diffusion. Gmyrek et al. (2025) further emphasize that occupational exposure varies by tasks and context and that transformation, rather than complete replacement, is a central concern. Benefits and losses may thus coexist within the same labour market.

The divide between adoption and productive application may be particularly salient in regions with expensive connectivity, intermittent electricity, limited devices or inadequate training. Even highly motivated individuals may be unable to use cloud-based systems consistently. These constraints can produce unequal returns: those with higher incomes and stronger technical skills may enjoy advantages, while disadvantaged groups remain excluded. This study therefore considers perceived barriers as integral to interpreting employment associations rather than as peripheral adoption problems.

Integrated Theoretical Framework

The analytical framework combines three complementary perspectives. First, human capital theory predicts that education and acquired competencies can enhance the productive value of AI-supported work (Becker, 1993). Second, the Unified Theory of Acceptance and Use of Technology identifies performance expectancy, effort expectancy, social influence and facilitating conditions as determinants of technological use (Venkatesh et al., 2003). In Jalingo, facilitating conditions plausibly include internet affordability, electricity, access to devices and appropriate training.

Third, the automation–augmentation perspective recognizes the tension between technologies that substitute human tasks and those that complement existing skills (Raisch & Krakowski, 2021). The resulting integrated model treats AI adoption as potentially associated with employment, employability, earnings and entrepreneurship, while expecting resources, skills and sectoral opportunities to shape these relationships. Because the supplied results are observational, these theoretical mechanisms are interpretations to be tested rather than mechanisms established by the available tables.

METHODOLOGY

The study adopted a quantitative cross-sectional survey design to examine the relationship between artificial intelligence (AI) adoption and youth employment outcomes in Jalingo Metropolis, Taraba State, Nigeria. The study focused on young people aged 18–35 years, with an analytical sample of 594 respondents. Data were obtained through a structured questionnaire designed to assess respondents' socio-demographic characteristics, AI adoption, digital skills, employment participation, perceived employability, income generation, entrepreneurial activities and barriers to AI utilisation. The survey covered respondents with different educational backgrounds, employment experiences and levels of exposure to AI technologies. However, the sampling frame, respondent selection procedure, fieldwork dates, sample-size determination and response rate require confirmation from the original field records to establish the representativeness and reproducibility of the findings.

The research instrument incorporated measures of AI utilisation, digital skills, perceived employability, perceived opportunities and challenges associated with AI adoption. AI utilisation was measured on a 0–4 scale, while digital skills, perceived employability, opportunities and barriers were assessed using five-point response scales. The internal consistency of the reported multi-item measures was evaluated using Cronbach's alpha (Cronbach, 1951). The reliability coefficients were 0.954 for AI utilisation, 0.833 for digital skills, 0.832 for perceived employability and 0.644 for perceived AI opportunities. Although the digital-skills and employability measures demonstrated satisfactory internal consistency, the AI-utilisation scale requires examination for possible item redundancy, while the opportunities scale requires further assessment of its

reliability. The questionnaire items, instrument validation procedures and ethical arrangements should be verified against the original research documentation.

Data analysis involved descriptive and inferential statistical techniques. Frequencies, percentages, means and standard deviations were employed to summarise respondents' characteristics, AI adoption patterns and perceived barriers. Binary logistic regression was used to examine associations between AI adoption and employment participation and entrepreneurial engagement, while ordinary least squares (OLS) regression assessed the relationship between AI adoption and perceived employability. A separate OLS model using logarithmically transformed earnings examined income differences among respondents with positive earnings. Statistical significance was evaluated at the 0.05 level, with effect estimates reported alongside 95% confidence intervals. The four research hypotheses were assessed using the corresponding regression models. Nevertheless, the original model outputs, adjustment variables, missing-data procedures and diagnostic results require verification before the statistical estimates can be treated as independently reproducible. Given the cross-sectional design, the findings were interpreted as statistical associations rather than evidence of causal relationships.

RESULTS AND INTERPRETATION

Respondents' Demographic Characteristics and AI Utilisation

Table 1: Demographic Characteristics, AI Adoption and Economic Activities of Respondents (n = 594)

Characteristics	**Frequency**	**Percentage (%)**
Sex		
Male	329	55.4
Female	265	44.6
Age		
18–24 years	212	35.7
25–35 years	382	64.3
Educational qualification		
Tertiary qualification	354	59.6
Employment and economic activities		
Worked for pay/profit in the last seven days	353	59.4
Operated a business	175	29.5
Artificial intelligence adoption		
Ever used an AI application	298	50.2
Used AI in the preceding 30 days	293	49.3
Received digital-skills training	316	53.2
Earned income from AI-supported work in the last month	120	20.2

Source: Study summary statistics (n = 594). Percentages are based on the total sample.

Table 1 presents the demographic characteristics, employment status and AI utilisation patterns of the 594 respondents. The findings indicate that 329 respondents (55.4%) were male, while 265 (44.6%) were female. Regarding age distribution, 382 respondents (64.3%) were between 25 and 35 years, compared with 212 (35.7%) aged 18–24 years. Furthermore, 354 respondents (59.6%) possessed tertiary educational qualifications. In terms of economic participation, 353 respondents (59.4%) reported engaging in paid employment or profit-generating activities during the preceding seven days, while 175 (29.5%) operated businesses. These findings indicate that the sample comprised young people with varying educational backgrounds and forms of economic engagement.

Regarding AI adoption, 298 respondents (50.2%) had previously used AI applications, while 293 (49.3%) reported using AI within the preceding 30 days. Additionally, 316 respondents (53.2%) had received digital-skills training. However, only 120 respondents (20.2%) reported earning income through AI-supported activities during the preceding month. This finding reveals a substantial difference between AI adoption and direct economic utilisation, suggesting that familiarity with AI applications does not necessarily translate into income-generating opportunities. The results further highlight the importance of examining digital competencies, infrastructural barriers and access to employment opportunities in understanding the economic implications of AI adoption among young people in Jalingo Metropolis.

Scale Summaries and Internal Consistency

Table 2: Descriptive Statistics and Reliability Coefficients of the Study Variables

Study Variables	Mean	Standard Deviation	Cronbach's Alpha (α)
AI utilisation (0–4)	1.11	1.31	0.954
Digital skills (1–5)	3.13	1.03	0.833
Perceived employability (1–5)	3.27	1.04	0.832
Perceived AI opportunities (1–5)	3.68	0.75	0.644

Source: Study summary statistics (n = 594).

Table 2 presents the descriptive statistics and internal consistency coefficients of the major study variables. The findings reveal that AI utilisation recorded a mean score of 1.11 (SD = 1.31) on a 0–4 scale, indicating relatively low average AI engagement among respondents, although its precise interpretation depends on the construction of the measure. Digital skills recorded a mean score of 3.13 (SD = 1.03), while perceived employability had a mean score of 3.27 (SD = 1.04). Perceived AI opportunities recorded the highest mean score of 3.68 (SD = 0.75), indicating generally favourable perceptions of the economic opportunities associated with artificial intelligence. These findings suggest that respondents recognised the potential benefits of AI despite comparatively limited reported utilisation.

Regarding internal consistency, the AI-utilisation scale recorded a Cronbach's alpha coefficient of 0.954, while digital skills and perceived employability recorded coefficients of 0.833 and 0.832, respectively. The latter two coefficients indicate satisfactory internal consistency. However, the exceptionally high coefficient for AI utilisation (α = 0.954) warrants further examination of inter-item correlations and possible item redundancy. Conversely, the perceived AI opportunities scale recorded an alpha coefficient of 0.644, suggesting comparatively weak internal consistency and the need to examine item-total correlations and scale composition. Consequently, the reliability findings should be interpreted cautiously until the original questionnaire items and item-level statistical outputs have been reviewed.

4.3 Perceived Barriers to Artificial Intelligence Adoption

Table 3: Perceived Barriers to Artificial Intelligence Adoption among Respondents (n = 594)

Perceived Barriers	Mean	Standard Deviation	Agree/Strongly Agree (%)
High cost of internet access	4.22	0.91	80.3
Unreliable electricity supply	4.37	0.86	83.2
Limited access to digital devices	4.01	0.99	71.2
Inadequate AI-related training	3.68	1.08	59.4
Fear of employment displacement	3.25	1.15	43.6

Source: Study summary statistics (2026). Note: Mean scores are based on a five-point response scale. Agreement percentages represent respondents who selected Agree or Strongly Agree.

Table 3 presents respondents' perceptions of the major barriers affecting artificial intelligence adoption in Jalingo Metropolis. The findings reveal that unreliable electricity supply constituted the most frequently reported barrier, with a mean score of 4.37 (SD = 0.86), as 83.2% of respondents agreed or strongly agreed that it constrained AI utilisation. This was followed by the high cost of internet access (M = 4.22, SD = 0.91), identified by 80.3% of respondents, and limited access to digital devices (M = 4.01, SD = 0.99), reported by 71.2%. These findings suggest that infrastructural deficiencies and the affordability of digital technologies represent significant perceived obstacles to the effective utilisation of AI among young people in the study area.

Furthermore, inadequate AI-related training recorded a mean score of 3.68 (SD = 1.08), with 59.4% of respondents identifying insufficient training as a barrier to AI adoption. Fear of employment displacement recorded the lowest mean score of 3.25 (SD = 1.15), with 43.6% expressing concern about the possibility of AI replacing existing jobs. The findings indicate that respondents perceived infrastructural and technological accessibility challenges more strongly than employment displacement risks. This pattern is consistent with the Unified Theory of Acceptance and Use of Technology (UTAUT), which emphasises facilitating conditions as important determinants of technology adoption (Venkatesh et al., 2003). However, these results reflect respondents' perceptions rather than independently verified infrastructural conditions or actual job losses.

Overall, the findings suggest that expanding AI adoption and its potential economic benefits among young people in Jalingo Metropolis requires attention to reliable electricity, affordable internet connectivity, access to digital devices and practical AI-related skills development.

Multivariable Associations and Hypothesis Tests

Table 4: Regression Analysis of the Relationship between Artificial Intelligence Adoption and Youth Employment Outcomes

Employment Outcomes	Sample (n)	Reported Effect	95% Confidence Interval	p-value
Employment participation	594	aOR = 1.567	1.370–1.793	< .001
Perceived employability	594	β = 0.418	0.367–0.469	< .001
Earnings among positive earners	353	23.50%	+17.4% to +30.0%	< .001
Entrepreneurial participation	594	aOR = 1.596	1.380–1.845	< .001

Source: Reported regression summary from the study. Note: aOR = adjusted odds ratio; β = reported OLS regression coefficient; CI = confidence interval. Effects represent associations per one-point increase in the AI adoption score. Estimates remain subject to verification against the original statistical outputs.

Table 4 presents the reported multivariable associations between artificial intelligence adoption and youth employment outcomes in Jalingo Metropolis. The findings indicate a positive association between AI adoption and employment participation (aOR = 1.567, 95% CI: 1.370–1.793, $p < .001$), suggesting that a one-point increase in the AI adoption score was associated with 56.7% higher adjusted odds of employment participation. Similarly, AI adoption was positively associated with perceived employability (β = 0.418, 95% CI: 0.367–0.469, $p < .001$). If the reported coefficient is unstandardised, this represents a 0.418-point increase in perceived employability for every one-point increase in AI adoption, holding the model's adjustment variables constant.

Furthermore, the earnings model reported a positive association between AI adoption and income among respondents classified as positive earners (23.5%, 95% CI: 17.4%–30.0%, $p < .001$). This suggests that higher AI adoption was associated with greater reported earnings within the analysed subgroup, although the earnings measure, sample eligibility and logarithmic transformation require verification. Entrepreneurial participation also demonstrated a positive association with AI adoption (aOR = 1.596, 95% CI: 1.380–1.845, $p < .001$), representing 59.6% higher adjusted odds of business participation per one-point increase in the adoption score.

These findings suggest that AI adoption may be associated with favourable employment-related outcomes among young people in Jalingo Metropolis.

Hypothesis Decisions

The four null hypotheses formulated for the study were tested at the 0.05 level of significance using binary logistic regression and ordinary least squares (OLS) regression. The reported regression estimates and corresponding probability values were used to assess the statistical relationships between artificial intelligence adoption and youth employment outcomes in Jalingo Metropolis.

Table 5: Summary of Hypothesis Testing and Statistical Decisions

Null Hypotheses	Statistical Test	p-value	Decision
H_{01}: AI adoption has no significant relationship with employment participation among youths.	Binary logistic regression	< .001	Reject H_{01}*
H_{02}: AI adoption has no significant relationship with perceived employability among youths.	OLS regression	< .001	Reject H_{02}*
H_{03}: AI adoption has no significant relationship with earnings among youths with positive earnings.	Log-earnings OLS regression	< .001	Reject H_{03}*
H_{04}: AI adoption has no significant relationship with entrepreneurial participation among youths.	Binary logistic regression	< .001	Reject H_{04}*

Source: Reported regression summary (2026). Note: Significance level = 0.05. The asterisk indicates that decisions are provisional pending verification of the original regression outputs and model diagnostics.

Table 5 presents the statistical decisions regarding the four null hypotheses. The reported findings indicate that AI adoption was significantly associated with employment participation ($p < .001$), perceived employability ($p < .001$), earnings among positive earners ($p < .001$), and entrepreneurial participation ($p < .001$). Since the reported probability values were below the 0.05 significance threshold, all four null hypotheses were provisionally rejected. These results suggest statistically significant positive associations between AI adoption and the employment-related outcomes examined among young people in Jalingo Metropolis.

However, the rejection of these hypotheses does not establish that AI adoption directly improves employment opportunities, employability, earnings or entrepreneurial participation. The cross-sectional design permits the identification of statistical associations but cannot establish the direction of causality.

DISCUSSION OF THE FINDINGS

The findings revealed that artificial intelligence adoption was becoming increasingly prominent among young people in Jalingo Metropolis, with 50.2% of respondents reporting previous AI use and 49.3% indicating utilisation within the preceding 30 days. However, only 20.2% reported earning income through AI-supported activities, demonstrating a considerable gap between technological adoption and direct economic benefits. This finding supports human capital theory, which emphasises the importance of knowledge, skills and competencies in improving productivity and employment outcomes (Becker, 1993). It is also consistent with Anwar and Graham (2020), who observed that participation in digital labour markets does not automatically guarantee improved economic opportunities, particularly among African workers facing structural inequalities. The findings suggest that the economic value of AI adoption depends not merely on access to technology but also on the ability to apply digital competencies to productive and income-generating activities.

The regression results indicated positive associations between AI adoption and employment participation (aOR = 1.567, $p < .001$), perceived employability ($\beta = 0.418$, $p < .001$), earnings among positive earners (+23.5%, $p < .001$), and entrepreneurial participation (aOR = 1.596, $p < .001$). These findings are consistent with Noy and Zhang (2023), who established that generative AI could improve efficiency and performance in professional writing tasks, and Brynjolfsson et al. (2025), who demonstrated productivity improvements among customer-support workers using AI technologies. Similarly, Rajaram and Tinguely (2024) highlighted the opportunities

generative AI offers small and medium-sized enterprises through improved business operations and productivity. Nevertheless, the positive associations observed in the present study do not establish that AI adoption directly caused better employment outcomes, particularly because employed respondents and entrepreneurs may possess greater resources and incentives to adopt emerging technologies. The results also require verification against the original regression outputs before definitive statistical conclusions can be drawn.

The findings further established that unreliable electricity supply (83.2%), high internet costs (80.3%), limited

access to digital devices (71.2%) and inadequate AI-related training (59.4%) constituted the most frequently reported barriers to AI adoption. These findings support the Unified Theory of Acceptance and Use of Technology developed by Venkatesh et al. (2003), which identifies facilitating conditions as important determinants of technology adoption and utilisation. In the context of Jalingo Metropolis, infrastructural limitations and inadequate digital competencies may restrict young people's opportunities to participate effectively in AI-supported economic activities. Although fear of employment displacement received comparatively lower agreement (43.6%), this does not eliminate the possibility of technological disruption. Hui et al. (2024) documented adverse employment outcomes in certain online freelance occupations following the expansion of generative AI, while Gmyrek et al. (2025) emphasised the potential transformation of occupational tasks and employment structures.

From a theoretical perspective, the findings demonstrate the complementary relevance of human capital theory, UTAUT and the automation–augmentation perspective in explaining AI adoption and youth employment outcomes. Human capital theory highlights the importance of digital competencies in productive AI utilisation, while UTAUT explains how infrastructural and technological conditions influence adoption. The automation–augmentation perspective further illustrates how AI may complement existing human capabilities while simultaneously creating risks of occupational displacement (Raisch & Krakowski, 2021). Together, these perspectives suggest that the relationship between AI adoption and youth employment is shaped by the interaction of skills, technological accessibility and labour-market opportunities. Consequently, policies directed towards expanding AI-supported employment in Jalingo Metropolis should integrate practical digital-skills development, affordable technological infrastructure and inclusive entrepreneurial opportunities rather than concentrating exclusively on technological awareness.

POLICY IMPLICATIONS AND RECOMMENDATIONS

The findings of this study have important implications for youth employment, digital inclusion and economic development in Jalingo Metropolis, Taraba State. Although artificial intelligence adoption presents opportunities for employment, entrepreneurship and income generation, the findings indicate that technological utilisation does not automatically translate into economic benefits. Consequently, government agencies, educational institutions and development organisations should prioritise practical AI-related training that equips young people with market-relevant digital competencies. Such programmes should emphasise AI-assisted content creation, digital marketing, data management, online freelancing and entrepreneurship. This approach aligns with human capital theory, which recognises knowledge and skills as essential resources for improving productivity and economic participation (Becker, 1993).

Furthermore, addressing infrastructural barriers is essential for promoting inclusive AI adoption. The high levels of agreement concerning unreliable electricity supply (83.2%), internet costs (80.3%) and limited access to digital devices (71.2%) demonstrate the importance of improving technological accessibility. The Taraba State Government, in collaboration with relevant federal agencies, telecommunications providers and private-sector organisations, should consider establishing affordable digital innovation centres equipped with reliable electricity, internet connectivity and shared computing facilities. Universities and vocational training institutions should also strengthen partnerships with technology organisations to expand access to practical AI training, particularly among economically disadvantaged young people.

The study further recommends strengthening youth entrepreneurship and employment-support initiatives through the responsible integration of artificial intelligence. Institutions such as the National Directorate of

Employment (NDE), Small and Medium Enterprises Development Agency of Nigeria (SMEDAN), and relevant state employment agencies should consider incorporating AI-related business development, digital marketing and online service delivery into existing empowerment programmes. These initiatives should provide mentorship, entrepreneurial guidance and connections to potential clients rather than concentrating exclusively on technical training. Furthermore, appropriate safeguards should address data privacy, digital exploitation, job insecurity and potential occupational displacement. Such measures are consistent with the automation–augmentation perspective, which recognises both the productive opportunities and employment risks associated with technological advancement (Raisch & Krakowski, 2021).

Finally, policymakers should establish monitoring and evaluation mechanisms to assess whether AI-related interventions produce measurable improvements in employment participation, earnings, business performance and job quality. Particular attention should be given to young people with limited educational qualifications, inadequate digital skills and restricted access to technological resources. Future research should employ longitudinal or quasi-experimental approaches to determine whether AI adoption contributes to sustained employment and economic advancement. These measures would support more inclusive digital transformation and align with the broader objectives of Nigeria's National Artificial Intelligence Strategy (Federal Ministry of Communications, Innovation and Digital Economy, 2025).

CONCLUSION

This study examined the relationship between artificial intelligence adoption and youth employment outcomes in Jalingo Metropolis, Taraba State, Nigeria, with particular emphasis on employment participation, perceived employability, earnings and entrepreneurship. The findings revealed that although approximately half of the respondents had adopted AI technologies, only 20.2% reported generating income through AI-supported activities. The reported regression results indicated positive associations between AI adoption and employment-related outcomes, while unreliable electricity supply, high internet costs, limited access to digital devices and inadequate training emerged as major perceived barriers. These findings demonstrate that technological adoption alone is insufficient to guarantee meaningful economic opportunities without the necessary skills, infrastructure and access to productive markets.

The study contributes to the understanding of AI adoption and youth employment by integrating human capital theory, the Unified Theory of Acceptance and Use of Technology (UTAUT), and the automation–augmentation perspective. Human capital theory explains the importance of digital competencies in enhancing productive engagement, while UTAUT highlights the infrastructural and institutional conditions influencing technology utilisation. The automation–augmentation perspective further illustrates the opportunities and potential employment risks associated with AI-driven technological transformation. Collectively, these perspectives suggest that the economic benefits associated with AI adoption depend on the interaction between individual capabilities, technological accessibility and labour-market conditions. Consequently, policies should prioritise practical digital-skills development, affordable technological infrastructure, inclusive entrepreneurship and employment-support programmes. Nevertheless, the cross-sectional design limits causal interpretation, and the reported regression estimates require verification against the original statistical outputs. Future studies should employ longitudinal approaches to examine the long-term implications of AI adoption for youth employment, income security and sustainable economic development.

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