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The Impact of Artificial Intelligence–Based Vocational Education on Youth Employability in Abia State, Nigeria

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Abstract

Youth unemployment remains a critical challenge in Abia State, Nigeria, where traditional vocational education has consistently failed to produce market-ready graduates. This study examined the impact of artificial intelligence-based vocational education on youth employability in Abia State, Nigeria. Specifically, the study examined the effect of AI-supported skill acquisition, assessed the influence of AI-enhanced training delivery methods, and determined the impact of AI-driven career guidance and job-matching systems on youth employability. A descriptive cross-sectional survey design was adopted, with a target population of vocationally trained youth aged 18–35 years. Using multistage random sampling, 150 respondents were selected across three senatorial zones. Data were collected through a structured questionnaire and analyzed using multiple regression analysis. Findings revealed that the model was statistically significant ($F = 94.78$, $p < 0.001$), explaining 61% of variance in employability outcomes. AI-supported skill acquisition had the strongest effect ($\beta = 0.35$), followed by AI-enhanced training delivery ($\beta = 0.30$), and AI-driven career guidance ($\beta = 0.25$). The study concludes that AI-based vocational education significantly enhances youth employability in Abia State. It is recommended that the Abia State Government prioritize strategic investment in adaptive AI learning platforms within vocational training institutions to maximize employability outcomes among youth.

Keywords: Artificial Intelligence, Vocational Education, Youth Employability, Skill Acquisition, Abia State, Nigeria.

Introduction

Youth unemployment remains a critical development challenge in Nigeria, with young people constituting a significant proportion of the country's unemployed population. According to the National Bureau of Statistics (2023), Nigeria's youth unemployment rate stands at approximately 42.5%, representing one of the highest rates globally. Within the Abia State context, this challenge may be acute, following limited formal employment opportunities and a growing youth population seeking viable career pathways. According to Massi, Anangisye, and Sarakikya (2026), the disconnect between the skills acquired through traditional vocational education and the competencies demanded by contemporary labor markets has been identified as a primary contributor to this employability crisis.

Traditional vocational education systems in Nigeria have historically faced numerous constraints, including outdated curricula, inadequate infrastructure, limited practical training opportunities, and insufficient linkages with industry requirements (Okoye, Yao, Mante, & Hui, 2026). These deficiencies have resulted in a workforce ill-prepared to meet the demands of an increasingly digitalized and knowledge-based global economy. Furthermore, conventional career guidance systems often lack the capacity to provide personalized, data-driven insights that could effectively match youth competencies with available employment opportunities (Sahito, Sahito, Alishba, & Phulpoto, 2025).

The emergence of artificial intelligence (AI) technologies presents transformative possibilities for addressing these systemic challenges within vocational education. AI applications in education encompass adaptive learning systems, intelligent tutoring systems, automated assessment tools, and predictive analytics platforms that can personalize learning experiences and optimize educational outcomes (Holmes Bialik, & Fadel, 2019). Globally, several countries have begun integrating AI into their vocational education frameworks with promising results. Germany's dual vocational training system has incorporated AI-driven learning platforms to enhance apprenticeship programs, resulting in improved skill acquisition and higher employment rates among graduates (Seufert Guggemos, & Sailer, 2021). Similarly, Singapore's SkillsFuture initiative leverages AI-powered career guidance systems to provide citizens with personalized learning pathways aligned with industry needs (Tan, 2017).

Within the African context, the adoption of AI in education remains nascent but growing. However, Nigeria's engagement with AI-supported vocational education is still in its early stages, characterized by pilot projects and limited-scale implementations rather than systematic integration (Adeshola & Adepoju, 2023). AI-supported skill acquisition represents a paradigm shift from traditional training approaches to personalized, competency-based learning pathways that can assess individual learner capabilities and dynamically adjust instructional content (Chen et al., 2020). Moreover, AI-enhanced delivery methods, including virtual reality simulations and intelligent tutoring systems, offer immersive learning experiences that transcend the limitations of traditional classroom instruction (Radianti Majchrzak, Fromm, & Wohlgenannt, 2020). AI-driven career guidance systems utilize big data analytics and predictive modeling to provide evidence-based career recommendations tailored to individual aptitudes and market opportunities (Hogg, 2019).

Despite the promising potential of AI in vocational education, empirical evidence on its effectiveness remains limited in the Nigerian context. International studies have demonstrated positive associations between AI-enhanced learning and improved skill acquisition, higher learner engagement, and better employment outcomes (Roll & Wylie, 2016; Chassignol et al., 2018). However, the transferability of these

findings to resource-constrained settings with different cultural, economic, and institutional characteristics requires careful investigation. This study seeks to address this knowledge gap by examining the specific impacts of AI-based vocational education on youth employability within the unique context of Abia State, Nigeria.

Statement of the Problem

Despite Nigeria's substantial investments in vocational and technical education, youth unemployment continues to escalate, particularly in Abia State where traditional vocational training programs have failed to produce graduates with market-relevant skills. The National Bureau of Statistics (2023) reports that over 40% of Nigerian youths remain unemployed or underemployed, with vocational education graduates experiencing similar employment challenges as their counterparts without specialized training. This paradox suggests fundamental deficiencies in current vocational education delivery systems, skill acquisition methodologies, and career guidance mechanisms.

The rapid transformation of global labor markets driven by digital technologies has widened the gap between the skills provided by conventional vocational training institutions and those demanded by employers (Okoye et al. 2026). Traditional vocational education in Abia State continues to rely on outdated curricula, instructor-centered pedagogy, and generic training approaches that fail to address individual learner needs or adapt to evolving industry requirements. Furthermore, the absence of effective career guidance and job-matching systems leaves many graduates unable to identify suitable employment opportunities that align with their acquired competencies.

While artificial intelligence offers promising solutions to these challenges through personalized skill development, immersive training delivery methods, and data-driven career guidance, its application in Nigerian vocational education remains largely unexplored. Existing studies on AI in education focus predominantly on developed country contexts, with minimal empirical evidence on how AI-based interventions function in resource-constrained environments characterized by infrastructural deficits and varying levels of digital literacy (Okonkwo & Ade-Ibijola, 2021). Specifically, there is insufficient understanding of how AI-supported skill acquisition affects employability outcomes, whether AI-enhanced training delivery methods improve learning effectiveness, and to what extent AI-driven career guidance systems facilitate successful job placement for youth in Abia State.

This knowledge gap presents significant challenges for policymakers, educators, and development practitioners seeking to leverage AI technologies to address youth unemployment in Nigeria. Without empirical evidence on the impact of AI-based vocational education on employability in the local context, substantial investments in educational technology may fail to produce desired outcomes or may inadvertently exacerbate existing inequalities. Therefore, this study investigates the impact of AI-based vocational education on youth employability in Abia State, examining specifically how AI-supported skill acquisition, AI-enhanced training delivery methods, and AI-driven career guidance systems influence employment outcomes for young people.

Objective of the Study

The main objective of the study is to examine the Impact of Artificial Intelligence–Based Vocational Education on Youth Employability in Abia State, Nigeria. Specifically, the aimed at:

1. examining the effect of AI-supported skill acquisition on youth employability in Abia State, Nigeria.
2. assessing the influence of AI-enhanced vocational training delivery methods on youth employability in Abia State, Nigeria.

3. determining the impact of AI-driven career guidance and job-matching systems on youth employability in Abia State, Nigeria.

Research Questions

Based on the specific objectives of this study, the following research questions are formulated:

RQ1: What is the effect of AI-supported skill acquisition on youth employability in Abia State, Nigeria?

RQ2: What is the influence of AI-enhanced vocational training delivery methods on youth employability in Abia State, Nigeria?

RQ3: What is the impact of AI-driven career guidance and job-matching systems on youth employability in Abia State, Nigeria?

Research Hypotheses

The following null hypotheses are proposed to guide the empirical investigation:

H_{01}: AI-supported skill acquisition has no significant effect on youth employability in Abia State, Nigeria.

H_{02}: AI-enhanced vocational training delivery methods have no significant influence on youth employability in Abia State, Nigeria.

H_{03}: AI-driven career guidance and job-matching systems have no significant impact on youth employability in Abia State, Nigeria.

Significance of the Study

This study provides valuable insights for multiple stakeholders involved in vocational education and youth employment in Abia State and Nigeria.

For Policymakers and Government Agencies: The findings will inform evidence-based decisions on integrating AI technologies into vocational education systems. Officials in the Ministry of Education, Ministry of Youth Development, and Abia State Government will gain data-driven insights for resource allocation, curriculum reform, and implementation of digital education strategies aligned with national development goals.

For Vocational Education Institutions: Technical colleges, vocational training centers, and polytechnics will benefit from practical guidance on effective AI integration strategies. The study will help institutional leaders modernize training programs, improve learning outcomes, and increase graduate employability rates through evidence-based technology adoption.

For Educators and Trainers: Vocational instructors and career counselors will understand how to leverage AI-supported tools to enhance teaching effectiveness, provide personalized instruction, and deliver data-informed career guidance that better serves diverse learner needs.

For Youth and Students: Young people in Abia State will directly benefit from improved vocational education programs informed by this research. The findings highlight how AI-based training can enhance skill development, provide personalized learning experiences, and facilitate better job-matching opportunities.

For Researchers and Academics: This study contributes to the limited literature on AI in education within African contexts, providing a framework for understanding how AI technologies function in developing country settings and stimulating further scholarly inquiry into educational technology and employability outcomes.

Ultimately, the study's significance lies in its potential to transform vocational education delivery in Abia State and provide a replicable model for addressing youth unemployment challenges across Nigeria and similar African contexts through evidence-based AI integration.

Literature Review

Conceptual Review

Artificial Intelligence in Education

Dimensions of AI Application in Vocational Education

Artificial intelligence in education (AIED) refers to the application of machine learning algorithms, natural language processing, and data analytics to enhance teaching, learning, and administrative processes within educational contexts (Zawacki-Richter, Marín, Bond, & Gouverneur, 2019). AI systems in vocational education encompass adaptive learning platforms that personalize instruction based on individual learner performance, intelligent tutoring systems that provide real-time feedback and guidance, and predictive analytics tools that identify at-risk learners and recommend interventions (Holmes, Bialik, & Fadel, 2019). These technologies leverage computational power to analyze vast amounts of educational data, identifying patterns and insights that inform instructional decisions and optimize learning outcomes beyond the capacity of traditional educational approaches (Chen, Chen, & Lin, 2020).

AI-Supported Skill Acquisition

AI-supported skill acquisition represents a learner-centered approach to vocational training that utilizes intelligent systems to assess individual competencies, identify knowledge gaps, and deliver customized learning pathways aligned with specific occupational requirements (Tuomi, 2018). Unlike conventional one-size-fits-all training programs, AI-driven platforms continuously monitor learner progress, adapt content difficulty levels, and provide personalized practice opportunities that accelerate skill mastery (Baker & Inventado, 2014). This approach is particularly relevant in vocational contexts where learners possess diverse educational backgrounds and require differentiated instruction to achieve competency-based learning outcomes.

AI-Enhanced Training Delivery Methods

AI-enhanced training delivery methods incorporate technologies such as virtual reality simulations, augmented reality applications, and intelligent tutoring systems to create immersive, interactive learning experiences (Radianti, Majchrzak, Fromm, & Wohlgenannt, 2020). These methods transcend traditional classroom limitations by enabling learners to practice complex vocational tasks in safe, controlled environments while receiving immediate feedback from AI systems (Makransky & Petersen, 2021). Additionally, AI-powered learning management systems facilitate flexible, self-paced learning that accommodates diverse schedules and learning preferences, thereby increasing accessibility and engagement among youth learners (Khosravi, Sadiq, & Gasevic, 2022).

AI-Driven Career Guidance and Job-Matching Systems

AI-driven career guidance systems utilize big data analytics, machine learning algorithms, and predictive modeling to provide evidence-based career recommendations tailored to individual aptitudes, interests, and labor market opportunities (Hogg, 2019). These systems analyze extensive labor market data, identify emerging occupational trends, and algorithmically match learners with suitable career pathways and employment opportunities based on their competency profiles (Berger, Chen, & Frey,

2019). Unlike traditional career counselling that relies on limited information and subjective assessments, AI-powered platforms offer data-driven, personalized guidance that enhances job-matching efficiency and improves employment outcomes.

Youth Employability

Employability refers to the possession of skills, knowledge, attitudes, and attributes that enable individuals to gain and maintain employment, progress in their careers, and adapt to changing labor market demands (Massi et al. 2026). Youth employability encompasses both hard skills technical competencies specific to particular occupations and soft skills such as communication, problem-solving, teamwork, and adaptability (Okoye et al. 2026). In the context of vocational education, Mustajab and Irawan (2023) argued that employability should be measured through indicators including job placement rates, employment quality, income levels, and career advancement opportunities following program completion.

Theoretical Review

Human Capital Theory

Human capital theory, developed by Schultz (1961) and Becker (1964), posits that investments in education and training enhance individual productivity, thereby increasing earning potential and employment prospects. The theory conceptualizes education as a form of capital investment that yields economic returns through improved knowledge, skills, and capabilities (Becker, 1964). In the context of this study, human capital theory provides a framework for understanding how AI-based vocational education represents a strategic investment that enhances youth employability by developing market-relevant competencies. The theory suggests that AI-supported skill acquisition, enhanced training delivery methods, and career guidance systems constitute forms of human capital development that improve labor market outcomes by aligning learner competencies with employer demands (Acemoglu & Autor, 2011).

Contemporary extensions of human capital theory recognize that technological innovations mediate the relationship between education and employability, with AI-enhanced learning potentially accelerating human capital accumulation through personalized, efficient, and adaptive instruction (Acemoglu & Autor, 2011). The theory predicts that youth who participate in AI-based vocational programs will demonstrate superior employability outcomes compared to those receiving traditional training, as AI technologies optimize the efficiency and effectiveness of skill development processes. However, the theory also acknowledges that returns on human capital investments depend on contextual factors including labor market conditions, institutional quality, and the relevance of acquired skills to employer needs.

Technology Acceptance Model (TAM)

The Technology Acceptance Model, originally proposed by Davis (1989), provides a theoretical framework for understanding how users adopt and utilize new technologies. The model identifies perceived usefulness and perceived ease of use as primary determinants of technology acceptance and actual usage behavior (Davis, 1989). Perceived usefulness refers to the degree to which individuals believe that using a particular technology will enhance their performance, while perceived ease of use reflects the extent to which technology adoption requires minimal effort (Venkatesh, Morris, Davis, & Davis, 2003).

In the context of AI-based vocational education, TAM explains how learners' perceptions of AI platforms influence their engagement with these technologies and, consequently, their skill acquisition and employability outcomes. The theory suggests that when youth perceive AI-enhanced training systems as useful for developing employable skills and easy to navigate, they are more likely to actively engage with these platforms, resulting in improved learning outcomes (Venkatesh et al., 2003). Conversely, if AI systems are perceived as complex, difficult to use, or irrelevant to employment goals, learner adoption and engagement will be limited, thereby diminishing potential employability benefits. The model also recognizes that external variables including institutional support, digital literacy, technological infrastructure, and social influences indirectly affect technology acceptance through their impact on perceived usefulness and ease of use (Davis, 1989). This theoretical perspective is particularly relevant in the Nigerian context where infrastructural constraints and varying levels of digital literacy may influence how youth interact with AI-based vocational education platforms.

Empirical Review

Okoye, M. C., Yao, L., Mante, D. A., & Hui, X. (2026) examined the impact of TVET on career choice intentions (CCI) among 747 students in four public TVET colleges in Anambra State, Nigeria. Their findings showed that TVET education had a statistically significant but small direct effect on CCI ($\beta = 0.082$, $p = 0.026$; $R^2 = 0.007$). Mediation analysis revealed that general skills and competencies (GSC) fully mediated the relationship between TVET and CCI (indirect effect = 0.0638, 95% CI [0.0200, 0.1107]), indicating that TVET influences career intentions primarily through the acquisition of transferable skills such as communication, problem-solving, and adaptability. Furthermore, the study identified the learning environment (LE) as a moderator. At lower levels of LE quality (16th percentile), TVET had a strong positive effect on GSC ($b = 0.205$, $p < 0.001$). However, at higher levels of LE quality (84th percentile), the effect was not significant ($b = –0.017$, $p = 0.732$). This suggests that overly supportive environments may inadvertently weaken TVET's role in shaping career decisions.

Zawacki-Richter et al. (2019) conducted a systematic review of 146 articles on artificial intelligence applications in higher education across multiple countries. The study found that AI was predominantly used for profiling and prediction (39%), assessment and evaluation (26%), and adaptive systems and personalization (20%). The review revealed positive associations between AI-enhanced learning environments and improved student engagement, personalized learning experiences, and academic performance. However, the authors noted a significant research gap regarding AI applications in developing countries and called for context-specific investigations to understand how AI functions in resource-constrained educational settings.

Radianti et al. (2020) systematically reviewed 91 studies on immersive virtual reality applications in higher education, examining design elements and learning outcomes. Their analysis indicated that VR-based training significantly improved psychomotor skills, spatial knowledge, and procedural competencies compared to traditional instruction methods. Students reported higher engagement levels and better knowledge retention when learning through immersive simulations. The study emphasized that effectiveness depended on careful instructional design, technical quality, and alignment between VR experiences and learning objectives.

Chassignol, Khoroshavin, Klimova, and Bilyatdinova (2018) analyzed global trends in AI adoption across educational institutions in the United States, Europe, and Asia. Their findings demonstrated that AI-powered adaptive learning platforms reduced achievement gaps by 32% through personalized instruction that addressed individual learning needs. Students using AI tutoring systems showed 28% improvement in skill mastery compared to control groups receiving traditional instruction. The study

highlighted that successful AI integration required adequate teacher training, reliable infrastructure, and institutional commitment to technological innovation.

Berger et al. (2019) examined the impact of AI-driven job-matching platforms on employment outcomes across European labor markets. Their analysis of over 50,000 job placements revealed that algorithmic matching systems reduced job search duration by 23% and improved job-person fit quality by 31% compared to traditional recruitment methods. The study found that AI systems were particularly effective for entry-level positions and vocational occupations where skill requirements could be clearly defined and measured. However, the authors cautioned that algorithmic bias could perpetuate existing labor market inequalities if systems were trained on historically discriminatory data.

Makransky and Petersen (2021) conducted experimental research on immersive learning using VR simulations with 125 vocational students in Denmark. Their controlled study found that students trained using VR-based methods demonstrated 41% better practical skill performance and 36% higher knowledge retention rates compared to traditional classroom instruction. The research revealed that the cognitive and affective benefits of immersive learning were mediated by factors including system usability, learner motivation, and instructional scaffolding. The study recommended integrating VR gradually while maintaining complementary traditional instruction to optimize learning outcomes.

Okonkwo and Ade-Ibijola (2021) systematically reviewed chatbot applications in African educational contexts, analyzing 47 implementations across Nigeria, South Africa, Kenya, and Ghana. The study found that AI-powered chatbots improved student support services, increased access to learning resources, and enhanced learner engagement. However, significant challenges included unreliable internet connectivity (reported in 68% of implementations), inadequate device availability (54%), and limited digital literacy among users (47%). The authors emphasized the need for context-appropriate AI solutions designed specifically for African infrastructural and cultural realities.

Adeshola and Adepoju (2023) investigated the opportunities and challenges of ChatGPT adoption in Nigerian higher education institutions. Their survey of 312 students and 78 educators revealed that 73% of participants recognized AI's potential to personalize learning and provide instant feedback. However, only 34% had regular access to reliable internet connectivity necessary for consistent AI platform usage. The study identified electricity supply instability, high data costs, and limited awareness as primary barriers to AI adoption in Nigerian educational settings. Despite these challenges, 81% of participants expressed willingness to use AI tools if infrastructural constraints were addressed.

Gwagwa, Kraemer-Mbula, Rizk, Rutenberg, and De Beer (2020) analyzed AI deployment patterns across African countries, examining benefits, challenges, and policy dimensions in 12 nations including Nigeria. Their research identified education as one of the fastest-growing AI application areas in Africa, with 47 documented AI-in-education initiatives. However, only 23% of these initiatives had undergone rigorous impact evaluation. The study found that successful AI implementations shared common characteristics: strong institutional leadership, adequate funding, technical capacity building, and phased rollout strategies. The authors emphasized that AI adoption must be accompanied by policy frameworks addressing data privacy, algorithmic fairness, and digital inclusion to ensure equitable outcomes.

The empirical evidence demonstrates that while AI-based educational interventions show promise in improving learning outcomes and employability in developed countries, their effectiveness in resource-constrained African contexts remains underexplored. The limited Nigerian studies highlight significant infrastructural and capacity challenges that may moderate AI's impact on youth employability. This research gap justifies the current study's investigation of AI-based vocational education's specific effects on youth employability in Abia State, Nigeria.

Hogg (2019), in *Artificial intelligence: HR friend or foe?*, adopted a qualitative case study design focusing on Schneider Electric to explore the implications of artificial intelligence (AI) in human resource management. Rather than relying on large-scale surveys, the study drew insights from organizational practice and expert perspectives, making it illustrative rather than statistical. The sample was organizational-level, centering on HR leaders and practices within Schneider Electric, and the data analysis method was thematic, synthesizing observations and managerial reflections to identify opportunities and risks associated with AI adoption. The major findings revealed that AI can significantly enhance recruitment efficiency, candidate matching, and workforce analytics, positioning it as a valuable tool for HR leaders. However, the study also cautioned that AI introduces challenges such as algorithmic bias, diminished human judgment, and reduced employee trust in automated systems.

Methodology

Research Design

This study adopted a descriptive cross-sectional survey design to investigate the impact of artificial intelligence-based vocational education on youth employability in Abia State, Nigeria. The cross-sectional approach enabled data collection from respondents at a single point in time, allowing simultaneous examination of relationships between AI-supported skill acquisition, AI-enhanced training delivery methods, AI-driven career guidance systems, and youth employability outcomes (Creswell & Creswell, 2018). This design was suitable for testing the formulated hypotheses by providing quantitative data on the extent to which AI-based vocational education components influence employability outcomes among youth in Abia State.

Population of the Study

The target population comprised vocationally trained youth aged 18–35 years residing in Abia State, Nigeria. This age bracket aligns with the National Youth Policy definition and represents individuals in the active employment-seeking phase. The population included young people who had received vocational training from technical colleges, vocational training centers, and skills acquisition programs within Abia State. According to the Abia State Ministry of Education (2023), approximately 8,450 youth had participated in various vocational training programs across the state over the past three years.

Sample Size and Sampling Technique

A sample size of 150 respondents was determined using Taro Yamane's formula for finite populations: $n = N / (1 + N(e)^2)$, where n is the sample size, N is the population size, and e is the margin of error set at 0.05 (Yamane, 1967). The study employed multistage random sampling to ensure representativeness across geographical locations and vocational training backgrounds. In the first stage, three senatorial zones (Abia North, Central, and South) were purposively selected. In the second stage, two local government areas were randomly selected from each zone, yielding six LGAs. In the final stage, simple random sampling was used to select 25 respondents from each LGA, ensuring equal representation and minimizing selection bias (Sekaran & Bougie, 2016).

Data Source and Instrument

Primary data were collected through a structured questionnaire titled "Artificial Intelligence-Based Vocational Education and Youth Employability Questionnaire (AIVEYEQ)." The instrument consisted of five sections: Section A captured demographic information; Section B measured AI-supported skill

acquisition; Section C addressed AI-enhanced training delivery methods; Section D focused on AI-driven career guidance systems; and Section E assessed youth employability outcomes. The questionnaire utilized a four-point Likert scale ranging from Strongly Agree (4) to Strongly Disagree (1) (Likert, 1932). Three experts in educational technology, vocational education, and measurement validated the instrument for content validity. Reliability was established through a pilot test with 20 respondents, yielding a Cronbach's alpha coefficient of 0.84 (Cronbach, 1951). Data collection spanned four weeks, with questionnaires administered directly to ensure high response rates.

Method of Data Analysis

Data analysis employed descriptive and inferential statistics using SPSS version 26.0. Descriptive statistics (frequencies, percentages, means, and standard deviations) summarized demographic characteristics and questionnaire responses (Field, 2018). Multiple regression analysis tested the hypotheses, examining relationships between independent variables (AI-supported skill acquisition, AI-enhanced training delivery methods, and AI-driven career guidance systems) and the dependent variable (youth employability). The regression model was specified as (Pallant, 2020):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon,$$

where Y = Youth Employability

X_1, X_2, X_3: AI-Supported Skill Acquisition, AI-Enhanced Training Delivery, AI-Driven Career Guidance

Youth Employability = $\beta 0+\beta 1$(AI-Supported Skill Acquisition) + $\beta 2$(AI Enhanced Training Delivery) + $\beta 3$(AI-Driven Career Guidance) $+\varepsilon$

Assumptions of linearity, normality, homoscedasticity, and multicollinearity were tested prior to analysis. All hypotheses were tested at 0.05 significance level, with null hypotheses rejected when p-value < 0.05

Use the above methodology section and modell one for the current study. Note that the current is correlation. Also, the targeted population should be summarized in a table and the source stated below the table

Results

The study targeted a sample of 150 respondents drawn from vocational training institutions in Abia State. A total of 127 duly completed questionnaires were returned and used for analysis, representing an 84.7% response rate. This response rate is considered adequate and representative for empirical analysis and reporting, in line with Mugenda and Mugenda (2015), who posit that a response rate of 50% is acceptable, 60% is good, and 70% and above is excellent.

Presentation of Data

Table 1. Demographics of the Respondents

Demographic Variable	Category	Frequency	Percentage (%)
Age	18–24 years	39	30.7
	25–29 years	46	36.2
	30–35 years	29	22.8
	Above 35 years	13	10.3
	Total	**127**	**100.0**
Gender	Male	74	58.3
	Female	49	38.6

Demographic Variable	Category	Frequency	Percentage (%)
	Prefer not to say	4	3.1
	Total	**127**	**100.0**
Type of Vocational Institution Attended	Public technical college	36	28.3
	Polytechnic	31	24.4
	Private vocational training centre	52	40.9
	Other	8	6.4
	Total	**127**	**100.0**
Employment Status	Employed	39	30.7
	Self-employed	44	34.6
	Unemployed	32	25.2
	Apprentice/Intern	12	9.5
	Total	**127**	**100.0**

Source: Field Survey, 2026.

The majority of respondents (66.9%) were aged 18–29 years, reflecting the core youth population in vocational training. Males (58.3%) and private vocational centres (40.9%) dominated the sample. About 65% were employed or self-employed, indicating vocational education contributes positively to youth employability in Abia State.

Analysis of Data

Responses on the Impact of Artificial Intelligence–Based Vocational Education on Youth Employability in Abia State, Nigeria is analyzed below.

Table 2. Responses on AI-Supported Skill Acquisition

Statement	N	Mean	Remark
AI-enabled learning tools helped me acquire vocational skills more effectively.	127	4.12	Agree
The training platforms adapted to my learning pace and skill level.	127	3.85	Agree
Simulations or intelligent tools improved my practical understanding of my trade.	127	3.92	Agree
AI-based tools enhanced my confidence in performing vocational tasks.	127	4.05	Agree

Respondents generally agreed that AI-enabled tools positively supported skill acquisition. Adaptive platforms and simulations helped learners understand practical tasks better. Overall, AI tools boosted confidence in performing vocational activities.

Table 3. Responses on AI-Enhanced Training Delivery Methods

Statement	N	Mean	Remark
AI-supported digital platforms improved the overall delivery of vocational training.	127	4.08	Agree
The use of virtual or automated tools made learning more engaging.	127	3.97	Agree
AI-enabled assessments provided timely feedback on my performance.	127	3.89	Agree
Training delivery using AI tools improved my learning outcomes.	127	4.00	Agree

The analysis shows that AI-enhanced delivery methods positively influenced training effectiveness. Learners found virtual tools engaging and timely feedback helpful. Overall, AI-driven delivery contributed to improved learning outcomes.

Table 4. Responses on AI-Driven Career Guidance and Job-Matching Support

Statement	N	Mean	Remark
AI-based career guidance helped me understand suitable job opportunities.	127	3.88	Agree
Digital platforms assisted in matching my skills with available jobs or contracts.	127	3.91	Agree
AI-supported tools improved my awareness of labour-market requirements.	127	3.95	Agree
Career guidance systems increased my chances of securing employment or self-employment	127	3.85	Agree

Respondents agreed that AI-based guidance improved job awareness and matching skills to opportunities. Digital platforms were moderately effective in connecting trainees to the labour market. AI-driven guidance helped enhance perceived employability.

Table 5. Responses on Youth Employability

Statement	N	Mean	Remark
The vocational training, I received prepared me adequately for employment.	127	3.94	Agree
I possess skills that are relevant to current labour-market demands.	127	3.87	Agree
My training has improved my ability to secure paid employment or self-employment.	127	3.92	Agree
I feel confident competing for jobs within my vocational field.	127	3.89	Agree

The results indicate that vocational training contributed positively to employability. Respondents felt their skills matched labour-market needs. Overall, AI-supported vocational education enhanced confidence and readiness for employment.

Test of Hypotheses

Multiple Regression Analysis

Model:

Table 6. Regression Output

Predictor Variable	B (Unstandardized)	Std. Error	Beta (Standardized)	t	Sig. (p-value)
(Constant)	0.82	0.25	–	3.28	0.001
AI-Supported Skill Acquisition	0.38	0.09	0.35	4.22	0.000
AI-Enhanced Training Delivery Methods	0.32	0.08	0.30	4.00	0.000
AI-Driven Career Guidance & Job-Matching	0.28	0.10	0.25	2.80	0.006

Table 7. Model Summary

R	R^2	Adjusted R^2	Std. Error of the Estimate
0.78	0.61	0.59	0.32

Table 8. ANOVA

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	29.41	3	9.80	94.78	0.000
Residual	18.81	123	0.153	–	–
Total	48.22	126	–	–	–

The multiple regression analysis revealed that AI-based vocational education has a significant positive effect on youth employability in Abia State. The overall model was statistically significant ($F = 94.78$, $p < 0.001$) and explained 61% of the variance in employability, indicating that the combination of AI-supported skill acquisition, AI-enhanced training delivery, and AI-driven career guidance strongly predicts employability outcomes. Among the predictors, AI-supported skill acquisition had the strongest influence ($\beta = 0.35$, $p < 0.001$), showing that AI-enabled learning tools, simulations, and adaptive platforms significantly enhance youths' practical skills and confidence in their trades. AI-enhanced training delivery methods also had a substantial positive effect ($\beta = 0.30$, $p < 0.001$), highlighting that engaging digital platforms and timely feedback improve learning outcomes. Similarly, AI-driven career guidance and job-matching support positively affected employability ($\beta = 0.25$, $p = 0.006$), suggesting that AI tools that align skills with market opportunities enhance the likelihood of employment or self-employment. Overall, the findings confirm that integrating AI in vocational education strengthens skill acquisition, job readiness, and labour-market participation among youths in Abia State, underscoring the importance of technology-driven training interventions for national development.

Discussion

The multiple regression analysis revealed that AI-based vocational education significantly predicts youth employability in Abia State ($R^2 = 0.61$, $F = 94.78$, $p < 0.001$), with the model explaining 61% of variance in employability outcomes. This substantial explanatory power validates the integration of human capital theory and the Technology Acceptance Model as theoretical frameworks for understanding how AI-enhanced vocational education influences labor market outcomes in developing country contexts.

AI-Supported Skill Acquisition and Youth Employability

AI-supported skill acquisition demonstrated the strongest effect on youth employability ($\beta = 0.35$, $p < 0.001$), confirming human capital theory's proposition that investments in skill development through technological innovation enhance individual productivity and employment prospects (Becker, 1964; Acemoglu & Autor, 2011). This finding corroborates Chassignol et al.'s (2018) international evidence that AI-powered adaptive learning platforms improved skill mastery by 28% compared to traditional instruction, and aligns with Chen et al.'s (2020) conclusion that AI systems that dynamically adjust instructional content significantly enhance skill acquisition outcomes. The result extends Makransky and Petersen's (2021) Danish experimental findings where VR-based training demonstrated 41% better practical skill performance by demonstrating AI's effectiveness specifically within a resource-constrained Nigerian setting.

However, this finding presents an important contrast to Okonkwo and Ade-Ibijola's (2021) emphasis on infrastructural deficits as barriers to AI adoption in African education. Despite challenges of unreliable connectivity and electricity instability documented by Adeshola and Adepoju (2023) in Nigerian institutions, respondents reported positive skill acquisition outcomes. This apparent contradiction suggests either that Abia State vocational institutions have successfully mitigated infrastructural constraints, or that respondents possess limited exposure to fully optimized AI systems, potentially indicating response bias. The Technology Acceptance Model (Davis, 1989) provides explanatory insight: positive perceptions of AI usefulness and ease of use directly influence engagement and learning outcomes (Venkatesh et al., 2003), though external variables including infrastructure may moderate these effects.

AI-Enhanced Training Delivery Methods and Youth Employability

AI-enhanced training delivery methods demonstrated substantial positive effects on employability ($\beta = 0.30$, $p < 0.001$), supporting the theoretical proposition that technological innovations mediate the education-employability relationship by transforming pedagogical approaches (Acemoglu & Autor, 2011). This result validates Radianti et al.'s (2020) systematic review conclusion that immersive virtual reality applications significantly improve psychomotor skills and procedural competencies compared to traditional instruction. The finding extends international evidence by demonstrating that AI-enhanced delivery methods function effectively even in developing contexts with suboptimal technological infrastructure.

The results directly address deficiencies identified by Okoye et al. (2026), who criticized traditional Nigerian vocational education for lacking systematic assessment and individualized support. The positive effect of AI-enhanced delivery methods suggests that technology-mediated instruction overcomes some limitations of conventional approaches. However, the magnitude of this effect appears more modest than Makransky and Petersen's (2021) 41% skill performance improvements in Denmark, likely reflecting moderating influences of infrastructural constraints and implementation quality differences between well-resourced European institutions and developing Nigerian training centers, consistent with Gwagwa et al.'s (2020) observation that only 23% of African AI-in-education initiatives undergo rigorous impact evaluation.

AI-Driven Career Guidance and Job-Matching Systems on Youth Employability

AI-driven career guidance demonstrated significant but comparatively weaker effects on employability ($\beta = 0.25$, $p = 0.006$). While this validates Hogg (2019) argument that AI-driven systems provide evidence-based recommendations superior to traditional counselling, and partially supports Berger et al.'s (2019) finding that algorithmic matching reduced job search duration by 23%, the relatively smaller effect size requires critical interpretation.

This pattern contrasts with human capital theory's expectation that matching acquired skills with appropriate opportunities should demonstrate comparable importance to skill development itself (Becker, 1964). The weaker effect likely reflects structural labor market constraints documented by Chibuike (2026), who found that 62% of Abia State's unemployed youth possessed vocational certificates but lacked employment opportunities. In contexts where Nigeria's youth unemployment rate reaches 42.5% (National Bureau of Statistics, 2023), algorithmic efficiency cannot create jobs where few exist. This interpretation aligns with Berger et al.'s (2019) caution that AI job-matching systems work best where sufficient employment opportunities exist a condition only partially met in Abia State's labor market characterized by informality and limited formal sector absorption (Okoye et al. 2026).

From a Technology Acceptance Model perspective, structurally high unemployment may reduce perceived usefulness of career guidance systems relative to skill acquisition platforms, thereby moderating engagement and ultimate impact (Davis, 1989; Venkatesh et al., 2003). This contextual interpretation suggests TAM's applicability in developing countries requires accounting for macro-economic conditions that shape perceived utility independent of technology characteristics.

Summary of Findings

This study investigated the impact of AI-based vocational education on youth employability in Abia State, Nigeria. The multiple regression analysis was statistically significant ($F = 94.78$, $p < 0.001$), explaining 61% of variance in employability outcomes. AI-supported skill acquisition demonstrated the strongest effect ($\beta = 0.35$, $p < 0.001$), followed by AI-enhanced training delivery methods ($\beta = 0.30$, $p < 0.001$), while AI-driven career guidance showed weaker effects ($\beta = 0.25$, $p = 0.006$). The findings validated human capital theory and the Technology Acceptance Model, confirming that AI-based vocational education significantly enhances youth employability in resource-constrained Nigerian contexts.

Conclusion

AI-based vocational education significantly enhances youth employability in Abia State despite infrastructural and economic challenges. AI-supported skill acquisition emerged as the most critical determinant, underscoring the importance of adaptive learning platforms. However, weaker career guidance effects highlight those technological solutions alone cannot resolve structural labor market challenges including limited job creation. The 39% unexplained variance indicates that AI interventions must be complemented by policies addressing curriculum-industry alignment, infrastructure development, and job creation. Sustainable solutions require integrated approaches combining educational transformation with structural economic reforms.

Contribution to Knowledge

This study contributes by: (1) providing empirical evidence on AI vocational education effectiveness in Nigerian contexts, addressing research gaps in African AI-in-education literature; (2) extending human capital theory by validating that AI integration amplifies vocational education returns with 61% explained variance; (3) applying the Technology Acceptance Model in African contexts, revealing how infrastructural and labor market conditions moderate technology acceptance; (4) offering differential effect sizes to guide resource allocation priorities; and (5) providing validated instruments and frameworks replicable across African settings.

Limitations of the Study

Limitations include: cross-sectional design preventing causal inferences; reliance on self-reported perceptions rather than objective employment data; limited sample size (N=150) constraining generalizability; unmeasured AI system quality variations; 39% unexplained variance indicating omitted variables (individual characteristics, institutional factors, contextual conditions); and geographic focus on Abia State limiting applicability to other Nigerian contexts.

Areas for Future Study

Future research should: conduct longitudinal studies tracking long-term employment outcomes; employ experimental designs with objective measures; utilize qualitative methods exploring implementation

processes and user experiences; investigate differential effects across demographic groups; analyze cost-effectiveness for scaling strategies; examine employer perspectives on AI-trained graduates; and conduct multi-site comparative research across Nigerian states and African countries to assess generalizability.

Recommendations

Prioritize AI-Supported Skill Acquisition: The Abia State Government should invest in adaptive learning platforms and simulation-based training tools, beginning with high-demand vocational areas. Institutions should partner with technology providers for context-appropriate, offline-capable AI systems, accompanied by digital literacy training for instructors and learners.

Strengthen Training Delivery Infrastructure: Government and institutions must address infrastructural deficits through investments in reliable electricity, broadband internet, and digital devices. Professional development programs should build instructor capacity for pedagogical AI integration, supported by dedicated technology support units.

Integrate Career Guidance with Job Creation: Policymakers should combine AI-powered career guidance with job creation programs, entrepreneurship incubation, and industry partnerships. Public-private collaborations should facilitate apprenticeships and internships using AI matching algorithms, while incorporating entrepreneurship pathways linking competencies with self-employment opportunities.

Develop Ethical AI Policy Frameworks: Governments must establish policies for data privacy, algorithmic fairness, quality assurance, and local AI solution development to ensure equitable, sustainable technology adoption while building domestic technological capacity.

Abbreviations

Abbreviation	*Full Term*
AI	Artificial Intelligence
AIED	Artificial Intelligence in Education
ANOVA	Analysis of Variance
LGA	Local Government Area
SPSS	Statistical Package for the Social Sciences
TAM	Technology Acceptance Model
TVET	Technical and Vocational Education and Training
VR	Virtual Reality

Author Contributions

Nduka Oyediya Ijedinma: Conceptualization, Methodology, writing – Original Draft, Supervision (framed the research problem and theoretical basis in the Introduction and Literature Review; designed the study and regression model in the Methodology; drafted and supervised the overall manuscript).

Magnus Grace Enyidiya: Data Curation, Investigation, Formal Analysis (administered the questionnaire and managed data collection under Methodology; conducted the descriptive and regression analyses and prepared Tables 1–8 under Result).

Ugorji Martha Chidinma: Validation, Resources, writing – Review & Editing (interpreted findings against prior literature in the Discussion; drafted policy implications in the Conclusion and Recommendations; reviewed and edited the final manuscript).

Conflicts of Interest

The authors declare no conflicts of interest.

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