

Adoption of AI Tools and their Effect on Women's Empowerment and Productivity in the Maize Value Chain of Zangon-Kataf LGA, Kaduna State, Nigeria

*** Laurretta C. Okwor and Augustine Mathias**

¹Department of Agricultural Education, Kaduna State College of Education, Gidan Waya

*Corresponding Author's email: okworlaurretta@gmail.com

Abstract

This study examines the adoption of artificial intelligence (AI) tools and their effects on women's empowerment and agricultural productivity within the maize value chain in Zangon-Kataf Local Government Area, Kaduna State, Nigeria. A survey design was employed using a multistage sampling technique; five wards, Zonkwa, Madakiya, Gidan Jatau, Zango Urban, and Kamantan were purposively selected based on their intensity of maize-related activities. At the final stage, 100 women were randomly drawn (20 per ward). Data were collected through validated structured questionnaires and interviews. Variables captured included socio-economic characteristics, adoption of AI tools (mobile weather apps, simple yield prediction software, mobile money platforms, digital marketplaces, and pest and disease diagnostic tools), productivity outcomes, empowerment indicators, and adoption constraints. Descriptive statistics, regression analysis, and empowerment indices were used for analysis. Findings revealed that about 62% of respondents adopted at least one AI tool, with mobile platforms (65%) and digital marketplace (60%) most widely used. Logit regression revealed that education level ($p < 0.05$), access to extension service (< 0.01), and farm size ($p < 0.05$) significantly influenced adoption. OLS estimates indicated that adoption of AI tools significantly improved market access, productivity, decision-making autonomy, and financial inclusion. However, adoption levels were modest due to constraints including high costs of smartphones and data, limited digital literacy, and weak extension support. The study concludes that AI tools significantly empower women while transforming the maize value chain (farming, processing and marketing). Recommendations include subsidizing digital access, enhancing digital literacy, expanding credit facilities, and improving rural infrastructure and extension services.

Keywords: Artificial intelligence, Women empowerment, Maize value chain, Digital tools, Kaduna State

1.0 Introduction

Artificial Intelligence (AI) has become a critical driver of transformation in global agriculture, reshaping how farmers produce, monitor, process, and market food. Nawaz *et al.* (2025) noted that AI tools particularly machine learning, deep learning, remote sensing, and agricultural robotics are now widely used to improve yield prediction, detect pests and diseases, optimize fertilizer use, and enhance supply-chain efficiency globally. Advancements in deep learning, diffusion models, and transfer learning have further accelerated innovation by enabling accurate crop monitoring even in data-scarce environments (Hu *et al.*, 2025; Hossen *et al.*, 2025). These developments have positioned AI as a core component of modern agrifood systems, enhancing productivity, operational efficiency, and environmental sustainability worldwide.

In sub-Saharan Africa, AI adoption within agriculture is growing but remains constrained by infrastructural and socio-economic limitations. Studies document increased use of smart farming technologies including drones, IoT sensors, and machine-learning-powered advisory platforms across West African countries, including Nigeria (Ikegwu *et al.* 2025). These tools support farmers in diagnosing crop stress, improving input use efficiency, and combating pests such as fall armyworm. However, scholars consistently note that limited connectivity, inadequate electricity, low digital literacy, and insufficient localized datasets hinder widespread AI deployment across African farming systems (Ahmed *et al.*, 2024). Gender disparities in access to technology are also pronounced; women farmers often have less access to digital tools, smartphones, training, and credit, which reduces their ability to adopt emerging agricultural innovations.

Nigeria is witnessing growing academic and practical interest in AI-driven agriculture. Research in the Nigerian context such as Yakubu *et al.* (2022), Ahmed *et al.* (2024), Akbar *et al.* (2023), and Ahmed and Adewumi (2023) shows that AI applications are emerging across several stages of the agricultural value chain, including crop monitoring, yield forecasting, pest/disease detection, automated irrigation, produce grading, and drone-based surveillance. These studies emphasize that AI has the potential to substantially improve agricultural productivity, strengthen food security, and reduce post-harvest losses.

Despite this expanding body of knowledge, a notable gap persists regarding the intersection of AI adoption, gender dynamics, and agricultural value chains in Nigeria. Women constitute a substantial share of the agricultural labor force in Kaduna State and play central roles in maize production from planting and weeding to processing, storage, and marketing. Yet women farmers typically have less access to technological innovations, training services, financial resources, and extension support compared to men. This limits their ability to benefit from AI-driven solutions that could improve yields, reduce labor burdens, enhance decision-making, and increase incomes. In maize value chains specifically, AI tools such as mobile-based advisory systems, remote-sensing crop monitoring, weather prediction services, automated pest-diagnosis applications, and price-forecasting platforms offer new opportunities to address long-standing productivity constraints. However, the extent to which women in rural areas such as Zangon-Kataf LGA are adopting these tools and benefiting from them remains understudied.

Understanding whether AI tools are being adopted, what factors influence their uptake among women, and how these tools affect women's decision-making power, income, labor efficiency,

and participation in the maize value chain is therefore essential. Against this backdrop, this study examines the adoption of AI tools and their effects on women's empowerment and productivity in the maize value chain in Zangon-Kataf LGA, Kaduna State.

The study is guided by the following research questions:

1. What are the socioeconomic characteristics of women in the maize value chain in Zangon-Kataf LGA?
2. What is the level of awareness and adoption of AI tools among these women?
3. How does adoption of AI tools affect empowerment and productivity outcomes?
4. What constraints limit adoption of AI tools in the maize value chain?

Accordingly, the main aim of the study was to examine the Adoption of AI Tools and their effect on Women's Empowerment and Productivity in the Maize Value Chain of Zangon-Kataf LGA, Kaduna State, Nigeria. The specific objectives were to:

1. Describe the socioeconomic characteristics of women farmers
2. Ascertain the level of awareness and adoption of AI tools
3. Analyze the effects of adoption on empowerment and productivity outcomes
4. Identify constraints limiting adoption

From these objectives, the following hypotheses were formulated:

H0₁: There is no significant relationship between socioeconomic characteristics and women's adoption of AI tools.

H0₂: Adoption of AI tools has no significant effect on women's empowerment in the maize value chain.

H0₃: Adoption of AI tools has no significant effect on productivity outcomes among women.

2.0 Materials and Methods

The research adopted a survey design, which allowed for systematic collection of quantitative data from women participants across the maize value chain. A multi-stage sampling technique was employed. At the first stage, Zangon-Kataf LGA was purposively selected due to its prominence in maize production. At the second stage, five wards Zonkwa, Madakiya, Gidan Jatau, Zango Urban, and Kamantan were purposively chosen based on the intensity of maize-related activities and the high concentration of women involved in the maize value chain. At the third stage, a random sampling procedure was applied to select 20 women participants (farmers, processors, and marketers) from each of the five wards, giving a total sample size of 100 respondents.

Data were collected primarily through a structured questionnaire and interview. The questionnaire captured respondents' socio-economic characteristics such as age, level of education, household size, farm size, income level, access to credit, and extension contact. It also assessed respondents' awareness and adoption of five AI tools relevant to the maize value chain: (1) mobile-based weather applications for climate information, (2) simple yield prediction software for planning and production decisions, (3) mobile money platforms for financial

inclusion and access to credit, (4) digital marketplaces for linking farmers and traders to wider buyers, and (5) pest and disease diagnostic tools for early detection and management of crop threats. Additionally, data were collected on productivity outcomes such as yield and income, empowerment indicators including decision-making roles, market access, financial control, and participation in group activities, as well as constraints associated with AI usage, such as limited digital literacy, infrastructural barriers, and affordability concerns.

For analysis, descriptive statistics including frequencies, percentages, and means were employed to profile socio-economic characteristics, levels of adoption of AI tools, and constraints encountered by women in the maize value chain. To further understand the dynamics of adoption, a Binary Logit regression model was employed to estimate the socio-economic and institutional factors influencing women's adoption of AI tools.

The Logit model uses a log-odds transformation. For the purpose of prediction, probability falls between 0 and 1 because adoption decisions are typically binary in nature (Salau *et al.*, 2017). The Logit model was chosen because the dependent variables in the adoption analysis (AI adoption) is binary i.e., respondents either adopted AI tools (1) or did not adopt them (0).

The model is expressed as:

$$\text{Logit}(P_i) = \ln(P_i / (1 - P_i)) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_n X_n + \mu_i \dots \dots \dots \text{Equation 2.1}$$

Where:

P_i is the probability of adopting AI tools, and $x_1 \dots x_n$ represent explanatory variables such as age, education, household size, farm size, credit access, and extension contact.

In addition, an Ordinary Least Squares (OLS) regression model was applied to determine the effect of AI adoption on women's empowerment outcomes. The functional form is specified as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_n X_n + \mu \dots \dots \dots \text{Equation 2.2}$$

Where:

Y denotes the empowerment index, constructed from composite indicators of productivity outcomes, decision-making capacity, market access, and financial control. The explanatory variables include socio-economic factors such as age, education, household size, farm size, access to credit, and AI tool adoption, while μ represents the error term.

The OLS model limits the explanatory variables to three (AI Adoption, farm size and education) to avoid multicollinearity risk and strengthens model stability because many of the socio-economic variables that measure age, household size, access to credit, cooperative membership and income are often highly correlated with farm size, education or AI adoption. Also, too many correlated predictors inflate standard error and distort coefficient estimates (Etaga, Ndubisi and Oluebube, 2021). These variables are widely recognized in agricultural productivity research as the core determinants of technology-driven productivity gains (Iheke *et al.*, 2024).

The research instrument was subjected to content validity checks through expert review and pilot-tested on 10 respondents outside the study area. Adjustments were made to improve clarity and relevance. Reliability of the empowerment index was confirmed using Cronbach's alpha, which indicated acceptable internal consistency. The priori expectation is that access to and adoption of AI tools would significantly improve women's empowerment in the maize value chain by enhancing their productivity, market access, and decision-making roles, despite the persistence of challenges associated with digital inclusion.

3.0 Results and Discussion

This section presents the findings of the study on the Adoption of AI Tools and their effect on Women's Empowerment and Productivity in the Maize Value Chain of Zangon-Kataf LGA, Kaduna State, Nigeria. The results are organized around the socio-economic characteristics of respondents, the level of adoption of AI tools, and the effects of AI adoption on women's empowerment. Both descriptive statistics and econometric analyses were employed to interpret the data, while tables are used to summarize the key outcomes.

Table 3.1: Socio-economic Characteristics of Respondents in Zangon-Kataf LGA

Variable	Category	Frequency (%)	Mean/Mode
Age (Years)	20–30	20	38
	31–40	35	
	41–50	30	
	>50	15	
Marital Status	Married	70	Married
	Single	10	
	Widowed	15	
	Divorced	5	
Household Size	1–4	25	6
	5–7	50	
	>7	25	
Education Level	No formal	10	Secondary
	Primary	20	
	Secondary	40	
	Tertiary	30	
Farming Experience	<5 years	20	10
	5–10 years	40	
	>10 years	40	
Primary Occupation	Farming	50	Farming
	Processing	30	
	Marketing	20	

Source: *Field survey, 2025*

The respondents in this study were primarily aged between 31–50 years, mostly married, with moderate to large household sizes averaging six persons per household and are similar to findings by Antia-Obong *et al* (2021) wherein household size also averaged six. A significant

portion (70%) had secondary or tertiary education, and over 80% had more than five years of farming experience, making them well-positioned to engage with technology.

Table 3.2: Awareness of AI Tools among Women in the Maize Value Chain

AI Tool	Aware (%)	Not Aware (%)
Mobile Weather Applications	80	20
Yield Prediction Software	70	30
Mobile Money Platforms	85	15
Digital Marketplaces	75	25
Pest and Disease Diagnostic Tools	60	40

Source: Field survey, 2025

Table 3.3: Adoption of AI Tools among Respondents

AI Tool	Adopted (%)	Not Adopted (%)
Mobile Weather Applications	65	35
Yield Prediction Software	55	45
Mobile Money Platforms	70	30
Digital Marketplaces	60	40
Pest and Disease Diagnostic Tools	40	60

Source: Field survey, 2025

Awareness of AI tools was generally high, especially for mobile money platforms (85%), weather apps (80%), and digital marketplaces (75%).

Actual adoption was lower (Table 3.3), with mobile money (70%) and weather applications (65%) being the most used. More complex tools like pest and disease diagnostic tools saw only 40% adoption, indicating an awareness–adoption gap likely influenced by other barriers.

Table 3.4: Effects of AI Adoption on Empowerment Indicators

Empowerment Indicator	Adopters (%)	Non-Adopters (%)
Control over Income	75	25
Decision-Making in Farming	70	30
Market Access & Bargaining Power	65	35
Access to Credit & Savings	60	40
Participation in Cooperatives	55	45

Source: Field survey, 2025

Empowerment indicators strongly favored AI adopters (Table 3.4). Women who adopted AI tools reported significantly higher control over income (75% vs. 25%), greater participation in

farming decisions (70% vs. 30%), and improved market access (65% vs. 35%). Similarly, access to credit, savings, and cooperatives improved among adopters, pointing to the role of AI in strengthening economic agency.

Productivity outcomes also confirmed these benefits (Table 3.5). AI adopters had higher average yields (3.2 tons/ha vs. 2.1), greater annual income (₦950,000 vs. ₦620,000), and reduced post-harvest losses (25% vs. 10%). These gains directly reflect the value of AI in improving farm efficiency and profitability.

Table 3.5: Productivity Outcomes of AI Adoption

Variable	Adopters	Non-Adopters
Average Yield (tons/ha)	3.2	2.1
Annual Income (₦)	950,000	620,000
Post-Harvest Loss Reduction (%)	25	10

Source: Field survey, 2025

Table 3.6: Constraints to Adoption of AI Tools

Constraints	Frequency (%)
High Cost of Smartphones/Data	70
Poor Digital Literacy	60
Unreliable Electricity Supply	55
Limited Extension Support	50
Cultural/Normative Barriers	40

Source: Field survey, 2025

Table 3.6 reveals persistent constraints that limit broader AI adoption among women. The most pressing barrier is the high cost of smartphones and data, reported by 70% of respondents. This is followed by poor digital literacy (60%), unreliable electricity supply (55%), and limited extension support (50%), all of which reflect infrastructural and knowledge-related gaps. Cultural and normative barriers were also cited by 40%, indicating that social norms may still discourage or restrict women's access to digital tools.

The binary logistic regression results (Table 3.7) identify the key socio-economic factors influencing women's adoption of AI tools in the maize value chain. Education, access to credit, and cooperative membership were all positive and statistically significant predictors. Specifically, education ($p = 0.01$) increased the likelihood of adoption, with an odds ratio of 1.57, indicating that educated women are 57% more likely to adopt AI tools. Access to credit ($p = 0.00$) and cooperative membership ($p = 0.01$) had even stronger effects, with odds ratios of 1.86 and 1.74 respectively, showing how financial and social capital are critical enablers. In

contrast, age and household size had no significant effect, suggesting that younger or older women, as well as those from smaller or larger households, are equally likely to adopt AI if other conditions are favorable.

Table 3.7: Binary Logistic Regression Results on Factors Influencing AI Adoption

Variable	Coefficient (B)	Std. Error	Odds Ratio	Sig. (p-value)
Age	-0.05	0.07	0.95	0.41
Education	0.45	0.12	1.57	0.01***
Household Size	0.08	0.11	1.08	0.25
Access to Credit	0.62	0.18	1.86	0.00***
Coop. Membership	0.55	0.15	1.74	0.01***

**Significant at 1% level. *Source: Field survey, 2025*

Table 3.8: OLS Regression Results on Effects of AI Adoption on Productivity

Variable	Coefficient (β)	Std. Error	t-value	Significance (p-value)
Constant	1.25	0.40	3.13	0.00***
AI Adoption	0.72	0.20	3.60	0.00***
Farm Size	0.35	0.10	3.50	0.01**
Education	0.28	0.09	3.11	0.01**

***Significant at 1%, *Significant at 5%. *Source: Field survey, 2025*

Table 3.9: Relationship between AI Adoption and Women's Empowerment

Variable	Coefficient (β)	Std. Error	t-Value	Sig. (p-value)
Constant	1.20	0.42	2.86	0.006
AI Adoption Index	0.38	0.09	4.22	0.000***
Access to resources	0.25	0.07	3.57	0.001**
Decision-making power	0.31	0.11	2.82	0.007**
Control over income	0.28	0.10	2.80	0.008**
Social participation	0.20	0.08	2.50	0.015*

$R^2 = 0.61$; $F(4, 45) = 12.74$; $p < 0.01$

Source: Field Survey, 2025; Regression Output

The OLS regression results (Table 3.8) show that AI adoption has a strong and significant positive effect on farm productivity. The constant term is 1.25 ($t = 3.13$, $p = 0.00^*$), indicating a

solid baseline for the model. AI adoption remains the strongest predictor, with a coefficient of 0.72 ($t = 3.60$, $p = 0.00^*$), demonstrating that increased use of AI tools substantially enhances productivity, even after controlling for other factors. Farm size also contributes significantly, with a positive coefficient of 0.35 ($t = 3.50$, $p = 0.01$), suggesting that larger landholdings are associated with higher yields. Education shows a similarly meaningful influence, with a coefficient of 0.28 ($t = 3.11$, $p = 0.01$), indicating that better-educated women are able to leverage AI technologies more effectively.

The regression results on table 3.9 show a clear and positive relationship between AI adoption and women's empowerment. The overall model is strong, explaining 61% of the variation ($R^2 = 0.61$), and is statistically significant ($F = 12.74$, $p < 0.01$). AI adoption emerges as the strongest predictor, with a coefficient of 0.38 and a highly significant p-value ($p = 0.000^*$), indicating that increased use of AI tools is strongly associated with higher empowerment levels among women. Access to resources also plays an important role, showing a positive effect ($\beta = 0.25$) and significance at $p = 0.001$, suggesting that women who have better access to financial or technological resources experience greater empowerment. Decision-making power contributes meaningfully as well, with a coefficient of 0.31 and $p = 0.007$, showing that women who participate more in household or community decisions tend to be more empowered. Similarly, control over income shows a positive and significant effect ($\beta = 0.28$, $p = 0.008$), indicating that financial autonomy strengthens empowerment outcomes. Social participation, though slightly smaller in effect, remains significant ($\beta = 0.20$, $p = 0.015$), highlighting the importance of women's involvement in social networks.

3.1 Discussion of Findings

3.1.1 Socioeconomic Characteristics of Women in the Maize Value Chain

The study revealed that the majority of women in Zangon-Kataf LGA were aged 31–50 years (65%), married (70%), and lived in moderate to large households (50% with 5–7 members). Education levels were relatively high, with 40% having secondary education and 30% tertiary education, while over 80% had more than five years of farming experience. Farming was the primary occupation for 50%, with processing (30%) and marketing (20%) also significant.

These characteristics suggest that women in this region are moderately educated and experienced, making them well-positioned to adopt AI tools in agriculture. Similar findings were reported by Adebayo *et al.* (2023) and Mwangi (2024), who observed that education and experience positively influence the capacity of women to engage with agricultural technologies. In contrast, studies by Okoro *et al.* (2021) indicated that age and household size sometimes limit engagement with digital tools. In this study, age and household size were not significant determinants, implying relatively equitable access to resources among different demographic groups.

3.1.2 Awareness and Adoption of AI Tools

Awareness of AI tools was generally high. The most recognized tools were mobile money platforms (85% aware), weather applications (80% aware), and digital marketplaces (75% aware), while yield prediction software (70% aware) and pest and disease diagnostic tools (60% aware) were less familiar. Despite high awareness, actual adoption was lower: mobile money

(70%) and weather applications (65%) were the most used, whereas pest and disease diagnostic tools saw only 40% adoption, highlighting an awareness–adoption gap.

Binary logistic regression showed that education (OR = 1.57, $p = 0.01$), access to credit (OR = 1.86, $p = 0.00$), and cooperative membership (OR = 1.74, $p = 0.01$) significantly increased the likelihood of adoption. Age and household size, however, were not significant. These findings are consistent with Hassan & Adekunle (2023) and Dube & Nwosu (2023), who reported that human and social capital are critical enablers of technology adoption. The lower adoption of complex tools, such as pest diagnostic applications, reflects findings by Otieno and Wamalwa (2024), who observed that complexity and poor digital literacy hinder uptake among smallholder farmers.

3.1.3 Effects of AI Adoption on Empowerment and Productivity

3.1.3.1 Empowerment Outcomes

Women who adopted AI tools reported higher levels of empowerment: control over income (75% adopters vs 25% non-adopters), decision-making in farming (70% vs 30%), market access (65% vs 35%), access to credit and savings (60% vs 40%), and participation in cooperatives (55% vs 45%). Regression results showed AI adoption as the strongest predictor of empowerment ($\beta = 0.38$, $p = 0.000$), followed by access to resources ($\beta = 0.25$, $p = 0.001$), decision-making power ($\beta = 0.31$, $p = 0.007$), control over income ($\beta = 0.28$, $p = 0.008$), and social participation ($\beta = 0.20$, $p = 0.015$), with the overall model explaining 61% of the variation ($R^2 = 0.61$, $F = 12.74$, $p < 0.01$).

These results align with Hassan & Adekunle (2023) and Mwangi (2024), who found that digital tools enhance women’s agency and social participation. However, the high magnitude of empowerment differs from Okoro *et al.* (2021) and Nkirote (2022), who reported that cultural norms and household restrictions often limit women’s decision-making in agricultural activities.

3.1.3.2 Productivity Outcomes

AI adopters achieved an average yield of 3.2 tons/ha compared to 2.1 tons/ha for non-adopters, with annual incomes of ₦950,000 vs ₦620,000, and post-harvest loss reductions of 25% vs 10%. Regression results indicate that AI adoption significantly enhances productivity ($\beta = 0.72$, $p = 0.00$), with farm size ($\beta = 0.35$, $p = 0.01$) and education ($\beta = 0.28$, $p = 0.01$) also positively influencing outcomes. These findings are consistent with Wekesa & Ng’etich (2024) and Abubakar (2023), who observed that digital tools improve yield, income, and efficiency. Contrastingly, Asare & Boateng (2023) reported limited productivity gains in areas with infrastructural challenges, highlighting the importance of enabling environments for AI adoption to translate into tangible productivity benefits.

3.1.4 Constraints Limiting Adoption of AI Tools

The major constraints reported were high costs of smartphones and data (70%), poor digital literacy (60%), unreliable electricity (55%), limited extension support (50%), and cultural or normative barriers (40%). These barriers mirror findings by Adamu (2022), Kabeer & Bello (2023), and FAO (2024), emphasizing that infrastructure, knowledge, and financial access remain critical challenges. Also, FAO (2024) similarly highlight affordability barriers, low digital skills, and infrastructural gaps as persistent obstacles to digital inclusion. The presence of

these barriers despite high adoption in some areas suggests that women in Zangon-Kataf may be adopting AI tools out of necessity or opportunity but still face systemic challenges that may limit long-term sustainability if not addressed.

4.0 Conclusion

The study concludes that AI adoption plays a transformative role in both women's empowerment and agricultural productivity within the maize value chain of Zangon-Kataf LGA. Women who adopt AI tools experience greater economic independence, enhanced decision-making power, improved access to markets and credit, and stronger social participation. At the same time, AI use significantly increases farm yields, income levels, and reduces post-harvest losses, demonstrating its practical value for livelihood improvement. However, adoption remains hindered by financial constraints, limited digital skills, poor infrastructure, and socio-cultural barriers. Addressing these challenges through expanded digital literacy programs, subsidized technology access, strengthened extension services, and supportive community structures can accelerate AI adoption and amplify its empowerment and productivity benefits.

4.1 Recommendations and Policy Implications

1. Nigerian Communications Commission (NCC), telecom operators, Kaduna State ICT Hub should formulate policy that will introduce subsidy schemes for smartphones and reduce data costs through public-private partnerships, aligning with the Federal Government's digital inclusion agenda.
2. Federal Ministry of Communications and Digital Economy, telecom providers should direct policy to expand broadband and mobile network coverage to agricultural zones to bridge the rural digital divide.
3. Kaduna Agricultural Development Agency (KADA), National Information Technology Development Agency (NITDA) and NGOs should incorporate digital literacy and AI training into agricultural extension services, with a special focus on women's groups.
4. Federal Ministry of Agriculture and Food Security, local cooperatives, research institutes should equip extension workers with AI-based tools and facilitate regular dissemination of digital advisory information, in line with FAO's call for "smart extension" services.

4.2 Limitations of the Study

The study is limited by its small sample size due to financial constraint to engage more areas of study and infrastructural challenges such as poor connectivity among others, which may affect the precision and generalization of the findings.

4.3 Areas of Further Research

1. Impact of specific AI tools on yield and labour efficiency.
2. Costs benefit analysis of AI adoption for smallholder women farmers.
3. Adoption of AI tools and their effect on productivity and empowerment in other Agricultural value chains.

References

- Abubakar, M. I. (2023). Digital technology adoption and productivity outcomes among smallholder farmers in northern Nigeria. *African Journal of Agricultural Economics and Rural Development*, 11(3), 88–102.
- Adebayo, K. S., Ogunleye, A. O. and Fagbemi, T. A. (2023). Socioeconomic determinants of women's participation in agricultural innovation systems in Nigeria. *Journal of Rural Social Sciences*, 38(2), 55–72.
- Adamu, S. L. (2022). Barriers to digital technology adoption among rural women farmers in Nigeria. *Journal of Agricultural Extension*, 26(4), 45–58.
- Ahmed, A. and Adewumi, A. O. (2023). Seasonal crop yield prediction in Nigeria using machine learning technique. *Journal of Artificial Intelligence and Applications*, 4(1), 55–67. <https://www.sabapub.com/index.php/jaai/article/download/728/383>
- Ahmed, M., Sulaiman, M., Adamu, A. and Musa, A. (2024). The role of artificial intelligence in modern farming system for achieving sustainable agricultural transformation in Nigeria. *Global Scientific and Social Research*, 6(1), 112–129. <https://www.jescae.com/index.php/gssr/article/view/996>
- Akbar, A., Ali, Z., Hussain, M. and Qaiser, I. (2023). Precision agriculture in Nigeria: The impact of AI on farming practices and sustainability. *Review of Agricultural Journals*, 15(2), 45–58. <https://zapjournals.com/Journals/index.php/rja/article/view/888>
- Anayo Chukwu Ikegwu, Chibueze Valentine Ikpo and Tosin Oladayo Akinwande (2025). Recent AI-based smart farming for monitoring and security in sub-Saharan Africa regions. *BOHR International Journal of Internet of things, Artificial Intelligence and Machine Learning*, 4(1), 10–18. DOI: 10.54646/bijiam.2025.27
- Antia-Obong, E. A., Hubbard, C. and Garrod, G. (2021). Influence of transaction costs on smallholder poultry market participation in Nigeria: A mixed-methods analysis. *World Food Policy*, 7(2), 96-110. <https://doi.org/10.1002/wfp2.12028>
- Asare, R. and Boateng, F. (2023). Adoption of digital agriculture technologies and productivity outcomes among smallholder farmers in Ghana. *International Journal of Agricultural Development Studies*, 8(1), 22–36.
- Dube, N. and Nwosu, E. (2023). Human and social capital as drivers of agricultural technology adoption in sub-Saharan Africa. *Agricultural Economics Review*, 24(1), 34–49.
- Etaga, H. O., Ndubisi, R. C. and Oluebube, N. L. (2021). Effect of Multicollinearity on Variable Selection in Multiple Regression. *Science Journal of Applied Mathematics and Statistics*, 9(6):141-153. <http://www.sciencepublishinggroup.com/i/sjams>.

- FAO. (2024). Digital agriculture and gender inclusion in Africa: Bridging the divide. Food and Agriculture Organization of the United Nations.
- Hassan, L. and Adekunle, A. (2023). Determinants of digital tool adoption among women farmers in Nigeria. *African Journal of Gender, Science and Technology*, 7(1), 14–29.
- Hossen, M., Awrangjeb, M., Pan, D. and Al Mamun, S. (2025). Transfer learning in agriculture: A review. *Artificial Intelligence Review*, 58, 1–29. <https://link.springer.com/article/10.1007/s10462-024-11081-x>
- Hu, Z., Li, Q. and Chen, Y. (2025). A comprehensive review of diffusion models in smart agriculture: Progress, applications, and challenges. arXiv:2507.18376. <https://arxiv.org/abs/2507.18376>
- Iheke, O. R., Oti, O. G. and Ukoha, V. C. (2024). Effect of Technology Adoption on Land Productivity among Arable Crop Farmers in Abia State, Nigeria. *Journal of Agricultural Economics, Extension & Science*, 10 (1), 46-63.
- Kabeer, N. and Bello, R. A. (2023). Gender, technology, and empowerment: Digital inclusion challenges in rural Africa. *Journal of Development Studies*, 59(5), 821–837.
- Mwangi, C. (2024). Women’s empowerment through digital agricultural technologies in East Africa: Evidence from Kenya. *Journal of Gender, Agriculture and Food Security*, 10(1), 1–18.
- Nawaz, A., Ullah, S., Ahmad, M. and Kamal, M. (2025). AI in agriculture: A survey of deep learning techniques for crops, fisheries and livestock. arXiv:2507.22101. <https://arxiv.org/abs/2507.22101>
- Nkirete, P. (2022). Gender norms and decision-making constraints among women farmers in East Africa. *International Journal of Gender Studies in Developing Societies*, 6(2), 110–125.
- Okoro, E. U., Chukwu, J. A., & Eze, C. (2021). Demographic factors influencing farmers’ adoption of ICT tools in southeastern Nigeria. *Nigerian Journal of Agricultural Extension*, 22(4), 100–113.
- Otieno, D. and Wamalwa, A. (2024). Digital literacy and the adoption of smart farming technologies among smallholders in Kenya. *African Journal of Information Systems*, 16(2), 45–61.
- Salua, S., Ajetomobi, J. and Dipeolu, A. (2017). Factors influencing adoption of improved agricultural technologies among women farmers in Nigeria. *Journal of Agricultural & Food Information*, 18(2), 143-158. doi:10.1080/10496505.2017.1285746

- Wekesa, A. and Ng'etich, K. (2024). Effects of mobile-based advisory services on crop productivity among smallholder farmers in sub-Saharan Africa. *International Journal of Agricultural Policy Studies*, 9(2), 33–47.
- Yakubu M, Yakubu U, Yakubu H and Mayun, F. A. (2024). The Effective Use of Artificial Intelligence in improving Agricultural Productivity in Nigeria. *Journal of Basics and Applied Sciences Research (JOBASR)* 2(4) DOI:<https://doi.org/10.33003/jobasr-2024-v2i4-68>