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Original Research Article

Artificial Intelligence in Agricultural Extension for Sustainable Livelihoods among Rural Farmers in Abuja, Nigeria

Ayodele Olajide Olawumi[1*], Beatrice Itoya Oyediji[2], Joseph Bamidele[3], Ugochinyere Princess Eleke[4], Mudashir Adeola Olaitan[4], Samson Olayemi Sennuga[4]

[1]Director, Federal Department of Agricultural Extension Services, Federal Ministry of Agriculture and Food Security, 3rd Floor, Bank of Agriculture Building, Central Area-Abuja

[2]Department of Agricultural Extension and Rural Development, Faculty of Agriculture University of Ibadan, Nigeria

[3]Faculty of Business and Law, University of Northampton, Waterside Campus, University Drive, Northampton NN1 5PH, United Kingdom

[4]Department of Agricultural Extension and Rural Sociology, Faculty of Agriculture, University of Abuja, FCT, P.M.B. 117, Abuja, Nigeria

***Corresponding Author**
Ayodele Olajide Olawumi
Director, Federal Department of Agricultural Extension Services, Federal Ministry of Agriculture and Food Security, 3rd Floor, Bank of Agriculture Building, Central Area-Abuja

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Abstract: This study investigated the role of Artificial Intelligence (AI) in agricultural extension for enhancing sustainable livelihoods among rural farmers in Abuja, Nigeria. Using a multi-stage sampling technique, data were collected from 200 respondents across five area councils. The socio-economic analysis revealed that 69% of farmers were male, with a mean age of 42.5 years and an average farm size of 2.1 hectares, and 42% reported access to extension agents. Findings on the role of AI tools indicated generally favourable responses, with the highest mean score recorded for "AI helps in making better farming decisions" (Mean = 3.13) and "AI improves weather-based planning" (Mean = 2.92). However, some skepticism remained, with lower mean scores reported for statements such as "AI tools reduce dependency on extension agents" (Mean = 2.37) and "AI optimizes resource use" (Mean = 2.35). Multiple regression analysis showed that age ($p = 0.004$), farming experience ($p = 0.005$), education ($p = 0.021$), cooperative membership ($p = 0.028$), contact with extension agents ($p = 0.013$), gender ($p = 0.053$) and farm size ($p = 0.055$) were significant predictors of AI adoption. Marital status was not significant ($p = 0.289$). Barriers to adoption were ranked using Kendall's Coefficient of Concordance ($W = 0.78$), with the top constraints being limited internet access (Mean Rank = 6.62), low digital literacy (5.86), and high device cost (5.74). The study concludes that while AI holds promise, its integration is shaped by socio-technical, infrastructural, and institutional factors.

Keywords: Artificial Intelligence, Agricultural Extension, Rural Farmers, Digital Adoption

INTRODUCTION

Agriculture plays a pivotal role in Nigeria's economy, particularly within rural communities, where it serves as both a primary livelihood source and a critical component of food security. The sector employs approximately 70% of the labour force and

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contributes about 22–25% to the country's Gross Domestic Product (GDP), underscoring its centrality in national development and poverty reduction strategies (FAO, 2022). However, agricultural productivity in Nigeria remains low by global standards due to a host of persistent challenges—among them climate variability, pest outbreaks, soil degradation, and limited access to finance, markets, and timely agronomic information. For decades, agricultural extension services have functioned as a key mechanism for supporting farmers through the dissemination of improved practices, technologies, and innovations developed by agricultural research institutions (Joel *et al.,* 2025). Yet, despite their strategic importance, Nigeria's public extension services have often been criticized for their limited reach, poor funding, and weak institutional support, which have collectively hindered their capacity to transform smallholder farming systems (Agbamu, 2021; Arokoyo, 2022). Extension agents are often too few in number, overburdened with administrative tasks, and unable to consistently deliver location-specific or timely advice, particularly to remote and underserved communities (Olaitan *et al.,* 2025).

Against this backdrop, Artificial Intelligence (AI) has emerged as a transformative technology with the potential to reshape how agricultural knowledge is generated, processed, and disseminated to farmers. AI refers to the simulation of human intelligence processes by machines, especially computer systems capable of learning, reasoning, and adapting over time. In agriculture, AI applications span a wide spectrum of uses, including predictive analytics for crop yield estimation, computer vision for pest and disease detection, machine learning algorithms for optimizing fertilizer and irrigation use, and natural language processing tools that facilitate personalized farmer communication (Kamilaris and Prenafeta-Boldú, 2018; Liakos, Busato, Moshou, Pearson and Bochtis, 2018).

Globally, agricultural advisory services are beginning to incorporate AI-driven platforms that can synthesize real-time environmental and agronomic data to provide location-specific recommendations to farmers, thus enhancing decision-making precision and reducing risks associated with climate uncertainty. In sub-Saharan Africa, innovative digital tools such as Precision Agriculture for Development (PAD), eSoko, and IBM's Agrolink are beginning to support smallholders by delivering automated messages, market updates, and crop management strategies via mobile phones and voice-based systems in local languages (Bulus, Chukwuma and Bawa, 2021; Adeyemi *et al.,* 2025). Nigeria is not an exception to this trend. Platforms such as Zenvus and Hello Tractor have demonstrated how AI can improve productivity by equipping farmers with data on soil conditions, rainfall forecasts, mechanization scheduling, and pest incidence. These platforms combine satellite imagery, sensor data, and machine learning models to generate actionable insights that are both scalable and cost-effective (Ojo, Adeyemo and Adegbite, 2020; Olusanya *et al.,* 2025).

The interconnection between agricultural extension, artificial intelligence, and sustainable livelihoods is therefore an area of growing academic and practical relevance. As Nigeria strives to achieve the Sustainable Development Goals (SDGs), particularly those related to zero hunger, poverty reduction, climate action, and industry innovation, AI-enabled extension services may offer a pathway toward more efficient and equitable agricultural systems (Idu *et al.,* 2025). However, realizing this potential depends on a nuanced understanding of how AI technologies interact with existing agricultural structures, socio-cultural norms, and institutional capacities. In particular, there is a need to evaluate whether AI-based advisory platforms can truly support the multidimensional components of sustainable livelihoods—namely, human, social, natural, financial, and physical capital—within rural Nigerian communities. Questions persist about the appropriateness, scalability, and long-term sustainability of such technologies when applied in heterogeneous farming environments with diverse crop systems, market structures, and governance regimes (Yunus *et al.,* 2025).

Moreover, concerns about dependency on foreign technology providers, data privacy, and digital sovereignty require serious consideration as AI systems become increasingly embedded in national food systems. As such, this study does not seek to provide a prescriptive blueprint for AI adoption in agriculture. Rather, it offers a critical, evidence-based evaluation of the extent to which AI can be integrated into Nigeria's agricultural extension architecture in ways that genuinely promote sustainable rural livelihoods. This study aims to evaluate the role of Artificial Intelligence in Agricultural Extension for Sustainable Livelihoods among Rural Farmers in Nigeria. To accomplish this, the following objectives are put forward to:

i. describe the socio-economic characteristics of rural farmers in the study area.
ii. assess the role of AI tools in enhancing the livelihoods of rural farmers in the study area.
iii. investigate the perceptions of rural farmers about AI in agricultural extension in the study area.
iv. analyse the factors influencing the adoption and effective utilization of AI technologies in agricultural extension services among rural farmers in the study area.

v. examine the barriers AI adoption for improving rural livelihoods in the study area.

LITERATURE REVIEW

Theoretical Framework

Sustainable Livelihoods Framework (SLF)

Developed by the UK Department for International Development (DFID) in the late 1990s, the Sustainable Livelihoods Framework offers a holistic and people-centered model for understanding how individuals and communities mobilize assets to achieve livelihood goals in the context of vulnerabilities and institutional constraints (Chambers and Conway, 1992; DFID, 1999). The SLF identifies five types of capital assets—human, social, natural, physical, and financial—as essential for sustaining livelihoods. These assets are influenced by external structures (e.g., policies, institutions, markets) and are used to pursue livelihood strategies that aim to improve well-being, reduce vulnerability, and enhance resilience.

In the context of this study, the SLF provides a robust foundation for assessing how AI-enhanced agricultural extension services contribute to sustainable rural livelihoods. For instance, AI applications that provide climate-smart farming advice, real-time pest alerts, or market price updates can enhance human capital by building knowledge and decision-making skills. Likewise, AI tools that improve access to inputs, machinery, or credit information support financial and physical capital, while platforms that facilitate networking or cooperative action may strengthen social capital. By applying the SLF, the study evaluates whether and how AI tools are aligned with the complex asset-based strategies rural farmers use to adapt and thrive within constrained agricultural environments. Moreover, the framework allows for the identification of inequalities in access to AI innovations—such as those based on gender, geography, or socio-economic status—that may inhibit their effectiveness in promoting inclusive development outcomes.

Conceptual Framework

The conceptual framework for this study, exploring the relationship between the independent variables and the dependent variable (Sustainable Livelihood Outcomes) being mediated by the intervening variables. The independent variables (socio-economic characteristics) in this study are factors or conditions that influence agricultural extension services. The intervening variables are contextual factors that can mediate or moderate the effect of AI technologies on rural livelihood outcomes. They include institutional and policy environment, market integration and pricing systems, affordability of AI-enabled services and availability of digital tools in rural areas.

MATERIALS AND METHODS

Study Area

Abuja, the Federal Capital Territory (FCT) of Nigeria, is located in the central region of the country and covers approximately 7,315 square kilometers. While known for its urban and administrative functions, Abuja also includes vast rural areas across six Area Councils: Abuja Municipal, Bwari, Gwagwalada, Kuje, Abaji, and Kwali. These rural districts are predominantly agrarian, with smallholder farmers cultivating staple crops such as maize, yam, cassava, and millet using traditional, rain-fed practices. Agriculture in rural Abuja faces persistent challenges, including limited access to extension services, low productivity, and exposure to climate variability. According to the FCT Agricultural Development Project (FCT-ADP, 2022), extension coverage remains inadequate, with many farmers lacking timely, scientifically informed advice. These conditions mirror broader national agricultural issues, making Abuja a representative site for examining the role of Artificial Intelligence in enhancing extension delivery. Abuja's combination of urban ICT infrastructure and rural digital exclusion makes it particularly suitable for studying disparities in technology adoption and the potential of AI-enabled agricultural systems. Additionally, its proximity to federal policymaking institutions creates opportunities to align local findings with national digital agriculture strategies. The region's socio-economic diversity and administrative significance thus provide a compelling context for investigating AI's contribution to sustainable rural livelihoods.

Population of the Study and Research Design

The target population for this study comprises rural smallholder farmers residing in the five agriculturally active Area Councils of the Federal Capital Territory (FCT), Abuja: Bwari, Gwagwalada, Kuje, Abaji, and Kwali. These councils are primarily rural, with agriculture serving as the main source of livelihood. The farmers in these communities are typically engaged in the cultivation of staple crops such as maize, cassava, yam, millet, and vegetables, and they rely on subsistence and low-input farming systems.

This study adopts a descriptive survey research design with a mixed-methods approach, combining quantitative and qualitative techniques. Structured questionnaires were used to collect quantitative data from farmers, focusing on demographics, AI adoption, role, and challenges. Qualitatively, semi-structured interviews and focus group discussions (FGDs) will be conducted with key stakeholders. These instruments will explore perceptions, barriers, and contextual factors influencing AI adoption and extension efficacy.

Sample Size and Sampling Techniques

This study employed a multistage sampling technique to select a total of 200 respondents from rural farming communities within the Federal Capital Territory (FCT), Abuja. The multistage approach was chosen to ensure that the sample captured the geographic, cultural, and agricultural diversity of the area while maintaining methodological rigor and logistical feasibility.

In the first stage, five out of the six Area Councils in the FCT were purposively selected based on their high concentration of smallholder farmers and predominantly rural characteristics. These Area Councils—Abaji, Bwari, Gwagwalada, Kuje, and Kwali—are known for their agricultural activities and represent key zones where extension services and technological interventions are most needed.

In the second stage, two rural farming communities were randomly selected from each of the five Area Councils, yielding a total of 10 communities. This step ensured geographic spread and helped capture variability in socio-economic conditions, farming practices, and access to extension services across the region.

In the final stage, 20 farmers were systematically selected from each of the 10 communities, making up the total sample of 200 respondents. The selection was based on household lists, farmer association registers, or local informant guidance, depending on community structure. Stratification was applied to ensure representation across gender and age groups, with only farmers who had resided in the area for at least two years and were actively engaged in agriculture considered eligible.

DATA COLLECTION

For this study, a structured questionnaire was used to collect primary data from rural crop farmers across selected communities in Abuja. Designed to capture detailed information on farmers' experiences with AI-enabled agricultural extension, the questionnaire was pre-tested through a pilot study involving farmers outside the main sample. This helped refine the instrument for clarity, relevance, and alignment with the study's objectives. Adjustments were made based on feedback to ensure its reliability and validity. Trained enumerators conducted face-to-face interviews, allowing respondents to fully understand the questions and provide accurate, in-depth responses within sessions averaging one hour.

Data Analysis

The data collected for this study were analyzed using a combination of descriptive and inferential statistical methods, based on the nature of each research objective. Descriptive statistics, including frequency distributions, percentages, and mean scores, were used to address Objective (i). A 4-point Likert scale was used to achieve Objective (ii and iii). Objective (iv) was analyzed using the Multiple Regression Model, to determine the strength and significance of multiple predictors affecting adoption behaviour. To address Objective (v), Kendall's Coefficient of Concordance (W) was used to measure the degree of consensus among respondents on ranked barriers. All statistical analyses were conducted using SPSS (Statistical Package for the Social Sciences), Version 24, ensuring robust and systematic data handling.

Model Specification

The 4-point Likert scale was used to assess farmers' perceptions, attitudes, and levels of agreement with various AI-related statements relevant to agricultural extension and livelihood outcomes. Respondents were asked to rate their agreement with each item using the following scale:

- Strongly Agree (SA) – 4
- Agree (A) – 3
- Disagree (D) – 2
- Strongly Disagree (SD) – 1
- To calculate the mean Likert score (X_s), the following formula was used:

$$X_s = \frac{\sum fn}{Nr}$$

Where:

- X_s= Mean Likert score
- Σ = Summation symbol
- F = Frequency of each Likert response (4, 3, 2, 1)
- n = Assigned Likert value for each response category
- Nr = Total number of respondents

A mean score threshold of 2.5 was adopted as the decision rule: responses with a mean score of ≥ 2.5 were interpreted as positive (agreement), while scores < 2.5 indicated negative (disagreement) perception or utilization.

Multiple Regression Model

To analyze Objective (iv)—which seeks to assess the factors influencing the adoption and effective utilization of Artificial Intelligence (AI) technologies in agricultural extension—a Multiple Regression Model was employed. This model estimates the relationship between a dependent variable and several independent (predictor) variables.

The model is specified as follows:
$Y=\beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + ... + \beta_nX_n + \varepsilon$
Where:

- Y = Level of AI adoption/utilization by farmers (dependent variable)
- β_0 = Intercept
- β1, β2, ..., βn = Coefficients of the independent variables
- X1, X2, ..., Xn = Predictor variables (e.g., age, education, access to extension, digital literacy, farm size, income, access to internet, training exposure)
- ε = Error term

Kendall's Coefficient of Concordance

To address Objective (v)— which explores the barriers to AI adoption for improving rural livelihoods, Kendall's Coefficient of Concordance (W) was employed. Kendall's W is calculated as follows:

$$W = \frac{12\ \sum(R_i - \bar{R})^2}{m^2\ (n^3 - n)}$$

Where:
W = Kendall's Coefficient of Concordance
R_i = Sum of ranks for each challenge
$\bar{R}$= Mean of the ranks
m = Number of respondents
n = Number of ranked challenges

RESULTS AND DISCUSSION

Socio-Economic Characteristics of Smallholder Farmers

The study revealed that 69% of the respondents were male, while 31% were female. This gender imbalance reflects broader agricultural labour trends in Nigeria, where men typically dominate land ownership and decision-making. Such disparities may limit women's access to AI-based agricultural innovations, as many digital extension platforms are channelled through male-centric networks, influencing the inclusivity of technology-driven extension systems (Auta, Abdullahi and Nasiru, 2020).

The results in Table 1 revealed that the mean age of farmers was 42.5 years, with 62% aged 31 and 50 years. This suggests a mature, economically active farming population. However, this group's accumulated farming experience may make them more receptive to AI tools that demonstrably improve productivity and reduce risks (Tambo and Wünscher, 2019).

The findings on marital status reveal that most farmers were married (76%), suggesting predominantly family-based farming units. Marital status may affect access to family labour, income distribution, and risk-sharing mechanisms (Adegbite *et al.*, 2021).

The results indicate that about 80.5% of the respondents had some formal education, with 32% attaining secondary and 20% tertiary education. Farmers with higher education levels are more likely to understand and apply AI-based recommendations, while low literacy levels may pose a barrier to digital technology adoption (Asadu, Anugwa and Onah, 2019).

The analysis of farming experience revealed that farmers had an average of 14.6 years of experience, with 63% having more than 10 years in farming. Experienced farmers often resist new technologies, preferring traditional methods (Tijani, Yusuf and Adetunji, 2022). Their deep understanding of local conditions provides a valuable foundation for integrating AI tools that enhance decision-making and productivity (Ogundari, 2023; Joel *et al.,* 2025).

The results reveal that the average farm size was 2.1 hectares, with 61.5% cultivating between 1 and 4 hectares. This indicates a predominance of smallholder farming. Small-scale farms often operate with limited resources and low resilience to climate shocks (Nkonya, Koo and Pender, 2020).

The results show that about 63.5% of farmers were members of cooperatives. Cooperative membership can improve exposure to AI technologies and increase trust in their use, particularly when tools are introduced through trusted group channels (Adesope, Ibrahim and Nwachukwu, 2022).

The results show that only 42% of farmers reported regular access to extension services, revealing a major gap in information dissemination. Limited contact with extension agents restricts farmers' awareness of and capacity to use new technologies (Agbamu, 2021).

Table 1: Socio-Economic Characteristics of Rural Farmers (n = 200)

Variable	Freq (n =200)	Percent
Gender		
Female	62	31.0
Male	138	69.0
Marital status		
Single	29	14.5
Married	152	76.0

Widowed	11	5.5
Divorced	8	4.0
Educational level		
No formal education	39	19.5
Primary school	57	28.5
Secondary school	64	32.0
Tertiary education	40	20.0
Age (Mean = 42.5 yrs)		
18 – 30 years	34	17.0
31 – 40 years	58	29.0
41 – 50 years	66	33.0
51 and above	42	21.0
Years of farming Experience (Mean = 14.6 yrs)		
< 5 years	23	11.5
5 – 10 years	51	25.5
11 – 20 years	74	37.0
Above 20 years	52	26.0
Farm Size (Mean = 2.1 ha)		
< 1 hectare	45	22.5
1 – 2 hectares	78	39.0
3 – 4 hectares	52	26.0
Above 4 hectares	25	12.5
Cooperative Membership		
Member	125	63.5
Non-member	73	36.5
Access to Extension Services		
Yes	84	42.0
No	116	58.0

Source: Field Survey, 2025

Farmers' Perceptions of the Role of AI in Mitigating Climate Change Impacts

The study found that respondents strongly agree that AI advisory platforms support better decision-making, with a mean score of 3.13. This aligns with Liakos *et al*. (2018), who observed that AI improves farm-level precision and efficiency, especially in input optimization and risk management.

The findings showed a mean score of 2.92, suggesting a positive perception of AI-enabled weather tools. Farmers reported greater ability to plan around rainfall patterns and seasonal variability. This reflects earlier research by Kamilaris and Prenafeta-Boldú (2018), which highlighted AI's potential in enhancing climate-smart agriculture through predictive meteorological services.

The findings indicated a mean score of 2.53, suggesting modest agreement that AI tools support income improvement. Farmers acknowledged limited yet growing access to real-time market information. This is consistent with Bulus *et al*. (2021), who reported that AI-driven marketing tools have the potential to strengthen smallholders' bargaining power and financial outcomes.

The findings revealed a mean score of 2.46, indicating a negative perception of farmers reporting that AI tools have not significantly improved extension relevance. This supports Adeleke, Osakwe and Hassan (2022), who found that poor digital infrastructure in rural Nigeria limits the accessibility of advanced agricultural technologies.

The findings showed a mean score of 2.37, reflecting respondents' disagreement with the notion that AI tools can replace traditional extension agents. Farmers may still value face-to-face interactions and human support. This aligns with Agbamu (2021), who emphasized the cultural and relational significance of extension officers in Nigeria's rural advisory systems.

The findings yielded a mean score of 2.35, indicating a negative perception of respondents not strongly associating AI tools with resource efficiency, possibly due to low exposure to precision farming technologies. Asadu *et al*. (2019) note that limited digital literacy and infrastructure often hinder the effectiveness of AI-driven tools in smallholder contexts.

The findings indicated a mean score of 2.48, suggesting skepticism about the effectiveness of AI in crop health management. Many respondents likely lack access to tools such as image-based diagnostic apps or smart sensors. Kamilaris and Prenafeta-Boldú (2018) similarly observed that AI's impact remains minimal in low-resource agricultural systems.

The findings showed a mean score of 2.53, indicating mild agreement on AI as contributing to sustainability. The relatively low consensus may reflect short-term usage or limited understanding of AI's long-term ecological benefits (Tambo and Wünscher, 2019; Maisule *et al.,* 2025).

Table 2: Respondents' Perceptions of the Role of AI Tools in Enhancing Rural Livelihoods

Statements	Strongly Agree (4)	Agree (3)	Disagree (2)	Strongly Disagree (1)	Mean Score (Xs)	Decision
AI-powered agricultural advisory platforms help me make better decisions on planting, input use, and pest control.	82 (41.0%)	76 (38.0%)	28 (14.0%)	14 (7.0%)	3.13	Accepted
AI-driven weather forecasting tools have improved my ability to plan farming activities and reduce climate-related losses.	65 (32.5%)	74 (37.0%)	41 (20.5%)	20 (10.0%)	2.92	Accepted
AI applications have helped me increase my farm income by providing timely market price information and sales strategies.	42 (21.0%)	58 (29.0%)	63 (31.5%)	37 (18.5%)	2.53	Accepted
Access to AI-enabled mobile apps and digital tools has made extension services more accessible and relevant to my specific farm needs.	39 (19.5%)	55 (27.5%)	65 (32.5%)	41 (20.5%)	2.46	Rejected
AI tools reduce my dependency on traditional extension agents by offering immediate and customized farming advice.	38 (19.0%)	47 (23.5%)	66 (33.0%)	49 (24.5%)	2.37	Rejected
AI technology helps me optimize resource use, including water, fertilizer, and seeds, thereby reducing waste and cost.	36 (18.0%)	50 (25.0%)	62 (31.0%)	52 (26.0%)	2.35	Rejected
AI-based pest and disease detection systems have improved the health and productivity of my crops.	44 (22.0%)	51 (25.5%)	61 (30.5%)	44 (22.0%)	2.48	Rejected
AI tools have played a key role in enhancing the sustainability of my farming practices and long-term livelihood resilience.	46 (23.0%)	54 (27.0%)	59 (29.5%)	41 (20.5%)	2.53	Accepted

Source: Field Survey, 2025

Factors Influencing AI Adoption among Rural Farmers

The model statistics in Table 3 suggest that the model diagnostics confirmed the regression model's validity. VIF values were below 2.5, indicating no multicollinearity. Residuals were normally distributed and homoscedastic, with linear relationships observed across predictors. The model was statistically significant ($F = 17.751$, $p < 0.001$) with strong explanatory power ($R^2 = 0.465$). Among the eight (8) factors tested, seven (7) factors had coefficients that were statistically meaningful: gender, age, educational level, farming experience, farm size, cooperative membership and contact with extension agents, while marital status was not statistically significant.

The findings revealed that gender had a positive and weakly significant influence on AI adoption at the 10% level ($p = 0.053$). Male respondents were more likely to adopt AI tools compared to females. This aligns with studies showing that men often have better access to resources and digital tools in rural Nigeria (Auta *et al*., 2020; GSMA, 2020).

The findings showed a significant negative relationship between age and AI adoption at the 1% level (p = 0.004). Older farmers were less likely to adopt AI technologies. This result supports earlier studies suggesting that younger farmers are more open to innovation and tend to engage more actively with digital agricultural tools (Tambo and Wünscher, 2019; Asadu *et al*., 2019).

The findings showed that education had a positive and significant influence on AI adoption at the 5% level (p = 0.021). Educated farmers were more likely to engage with AI-enabled platforms. This supports literature indicating that higher education improves digital literacy and understanding of complex tools, enhancing the likelihood of technology adoption (Asadu *et al*., 2019; Kamilaris and Prenafeta-Boldú, 2018).

The findings revealed a positive and highly significant relationship between farming experience and AI adoption at the 1% level (p = 0.005). More experienced farmers were more likely to adopt AI tools. This may reflect their accumulated exposure to agricultural innovations over time, confirming the role of experiential learning in technology uptake (Bulus *et al*., 2021; Ojo *et al*., 2020).

The findings showed a positive and weakly significant influence of farm size on AI adoption at the 10% level (p = 0.055). Farmers with larger landholdings were slightly more inclined to adopt AI. This supports prior findings that larger-scale farmers tend to adopt innovations earlier due to greater investment capacity (Nkonya *et al*., 2020; Adesope *et al*., 2022).

The findings indicated a positive and significant relationship between cooperative membership and AI adoption at the 5% level (p = 0.028). Farmers in cooperatives were more likely to adopt AI technologies. This aligns with previous research showing that cooperatives facilitate technology access through shared information, training, and peer influence (Adesope *et al*., 2022; Auta *et al*., 2020).

The findings showed that contact with extension agents had a positive and significant effect on AI adoption at the 5% level (p = 0.013). Farmers with regular extension contact were more likely to use AI tools. This supports evidence that extension services enhance awareness and credibility of new agricultural technologies (Agbamu, 2021; Mehmood, Ullah and Khan, 2021).

The findings indicated that marital status had no statistically significant effect on AI adoption (p = 0.289). This suggests that being married or single did not influence farmers' likelihood to adopt AI technologies. This result contrasts with some extension literature that links marital status with labour availability and decision-making, but confirms its limited role in technology uptake (Agbamu, 2021).

Table 3: Multiple Regression Analysis of Factors Influencing AI Adoption among Rural Farmers

Variable	Unstandardized Coeff. (B)	Standard error	Beta (β)	t-value	Sig. (p-value)
Gender	0.248	0.127	0.142	1.953	0.053*
Age (Years)	-0.021	0.007	-0.219	-2.952	0.004***
Marital Status	0.102	0.096	0.064	1.063	0.289
Educational Level	0.188	0.081	0.176	2.321	0.021**
Farming Experience (Years)	0.017	0.006	0.198	2.833	0.005***
Farm Size (Hectares)	0.114	0.059	0.125	1.934	0.055*
Cooperative Membership	0.164	0.074	0.148	2.216	0.028**
Contact with Extension Agents	0.205	0.082	0.171	2.500	0.013**
Number of Observation R (Multiple Correlation) R^2 (Coefficient of Deter.)	200.00 0.682 0.465				
Adjusted R^2	0.439				
F-statistic	17.751				
Sig. (F)	0.000				

Note: ***, ** and * indicate significance at 1%, 5% and 10% probability level respectively
Source: Field Survey, 2025

Challenges Faced in Accessing Quality Healthcare Services

The Kendall's Coefficient of Concordance (*W*) analysis yielded a coefficient value of 0.78, indicating a strong level of agreement among respondents regarding the ranking of key barriers to AI adoption. The associated Chi-square value (χ^2 = 100.14, *df* = 7, *p* < 0.001) confirms that this concordance is statistically significant, showing that these challenges are widely and consistently experienced across the study population.

The limited access to internet and digital infrastructure was identified as the most critical barrier to AI adoption, with a mean rank of 6.22. Farmers also cited inadequate broadband coverage, unstable electricity, and poor ICT infrastructure. Adeleke *et al*. (2022) found similar challenges across rural Africa, noting infrastructure gaps as major barriers to digital agricultural transformation.

The low level of digital literacy was identified as the second-most significant barrier, with a mean rank of 5.86. Farmers also cited their inability to navigate mobile applications or interpret AI recommendations. This supports Asadu *et al*. (2019), who emphasized that low ICT competence reduces the effectiveness of digital tools among rural farmers in Nigeria.

The high cost of smart devices and AI services was identified as the third-ranked barrier, with a mean rank of 5.74. Farmers also cited unaffordable smartphones, data plans, and AI-enabled tools. Bulus *et al*. (2021) found that economic constraints remain one of the most consistent obstacles to AI adoption in resource-limited farming systems.

Poor mobile network coverage was identified as the fourth major barrier, receiving a mean rank of 5.52. Farmers also cited irregular signal strength and poor connectivity in hard-to-reach villages. According to GSMA (2020), many rural communities in sub-Saharan Africa face limited network infrastructure, affecting the delivery of real-time AI services and digital advisories.

The lack of training and awareness about AI in agriculture was identified as the fifth-ranked barrier, with a mean rank of 5.38. Farmers also cited inadequate sensitization campaigns and limited training programs. Ojo *et al*. (2020) emphasized that without awareness and capacity building, rural farmers remain unaware of how AI can enhance agricultural productivity.

Language barriers and the absence of localized AI content were identified as the sixth-ranked barrier, with a mean rank of 5.21. Farmers also cited difficulty understanding English-only interfaces and a lack of local dialect support. Kamilaris and Prenafeta-Boldú (2018) found that digital tools are often not adapted to multilingual rural contexts, limiting their effectiveness.

Distrust in technology and fear of data misuse was identified as the seventh-ranked barrier, with a mean rank of 4.95. Farmers also cited concerns about surveillance, loss of data control, and misuse of personal farming information. Mehmood *et al*. (2021) noted that ethical concerns about data handling reduce trust and discourage AI use in agricultural contexts.

Inadequate government support and policy uncertainty were identified as the lowest-ranked barrier, with a mean rank of 4.63. Farmers also cited a lack of digital inclusion policies, weak institutional backing, and limited government incentives. Agbamu (2021) similarly observed that weak public-sector support often undermines innovation adoption in rural agricultural systems.

Table 4: Barriers to AI Adoption Ranked by Respondents Using Kendall's Coefficient of Concordance (*W*)

Barriers to AI Adoption	**Sum of Ranks (R_i)**	**Mean Rank ($\hat{R}$)**	**Rank Order**
Limited access to internet and digital infrastructure	1243	6.22	1st
Low level of digital literacy among rural farmers	1171	5.86	2nd
High cost of smart devices and AI-based tools	1148	5.74	3rd
Poor mobile network coverage in remote farming areas	1105	5.52	4th
Lack of training or awareness about AI applications in agriculture	1076	5.38	5th
Language barriers and lack of localized content in AI platforms	1042	5.21	6th
Distrust in technology and fear of data misuse	990	4.95	7th
Inadequate government support and unclear digital agriculture policies	925	4.63	8th
Kendall's *W*: 0.78 **Chi-Square Value: 100.14** **Degrees of Freedom (*df*): 7** **P-Value: 0.000 (Highly Significant)**			

Source: Field Survey, 2025

CONCLUSION AND RECOMENDATIONS

This study examined the role of Artificial Intelligence (AI) in agricultural extension and its contribution to sustainable livelihoods among rural farmers in Abuja, Nigeria. Drawing on data from 200 respondents across five agricultural zones, the analysis revealed important insights into farmers' socio-economic characteristics, their experiences with AI tools, patterns of adoption, and the systemic barriers shaping AI uptake.

The socio-economic profile showed that rural farming in Abuja is predominantly male-led (69%), with a majority of respondents being married (76%) and an average age of 42.5 years. Educational attainment was modest, with 32% having completed secondary education and 20% possessing tertiary qualifications. The mean farming experience stood at 14.6 years, while average farm size was 2.1 hectares, indicating a largely smallholder-based farming economy. Only 42% of farmers reported regular access to extension services, of which is vital for the effective use of AI-driven technologies.

Farmers expressed generally favourable views regarding the relevance of AI to their livelihoods. They acknowledged that AI tools enhanced decision-making, especially for tasks such as crop planning and climate forecasting. The highest-rated statements included "AI helps in making better farming decisions" (Mean = 3.13) and "AI improves weather-based planning" (Mean = 2.92). However, some skepticism remained, with lower mean scores reported for statements such as "AI tools reduce dependency on extension agents" (Mean = 2.37) and "AI optimizes resource use" (Mean = 2.35). These results highlight both the perceived potential and the limitations of AI tools in the eyes of end-users.

The multiple regression analysis identified the key factors influencing AI adoption. The model was statistically significant ($R^2 = 0.465$, $p < 0.001$), explaining approximately 46.5% of the variance in AI adoption. age ($p = 0.004$) and farming experience ($p = 0.005$) were significant at the 1% level, while educational level ($p = 0.021$), cooperative membership ($p = 0.028$), and contact with extension agents ($p = 0.013$) were significant at the 5% level. Farm size ($p = 0.055$) and gender ($p = 0.053$) were significant at the 10% level, whereas marital status showed no significant influence ($p = 0.289$).

Consensus around barriers was strong, with Kendall's Coefficient of Concordance ($W = 0.78$) indicating high agreement. Top-ranked constraints included limited internet access (Mean Rank = 6.22), digital illiteracy (5.86), and high cost of devices (5.74), while weak institutional support ranked lowest (4.63).

Based on the findings of this study, the following recommendations are proposed to enhance sustainable livelihoods among rural farmers using Artificial Intelligence (AI) in agricultural extension:

1. Given that limited internet access was the most significant barrier (Mean Rank = 6.22), it is essential that government agencies and private sector stakeholders invest in expanding broadband and mobile network coverage in underserved rural areas. Improved connectivity is foundational for accessing AI-driven agricultural platforms and services.
2. With a low level of digital literacy identified as a key constraint (Mean Rank = 5.86), targeted capacity-building initiatives should be implemented. These programs should focus on basic digital skills, smartphone usage, and how to interact with AI-enabled agricultural applications, particularly for less-educated and older farmers.
3. The high cost of smart devices and subscription-based platforms (Mean Rank = 5.74) limits AI adoption. Public-private partnerships should offer subsidies, instalment financing, or cooperative-based group access to reduce financial barriers and make digital tools more affordable for smallholder farmers.
4. The study showed that contact with extension agents significantly influenced AI adoption ($p = 0.013$). Therefore, traditional extension services should be equipped with AI tools and trained personnel to deliver hybrid advisory systems that combine digital and human support for increased farmer engagement.
5. The low ranking of institutional support (Mean Rank = 4.63) signals a policy gap. Government bodies should establish clear and inclusive regulatory frameworks for digital agriculture, ensuring data protection, equitable access, and support for digital extension innovations at the grassroots level.

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