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The Role of Artificial Intelligence (AI) in Enhancing Climate-Smart Agriculture and Knowledge Service Delivery among Smallholder Farmers in Kebbi State

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Abstract

Climate change continues to threaten agricultural productivity and the livelihoods of smallholder farmers in Kebbi State, Nigeria. Despite the promotion of climate-smart agriculture (CSA), many farmers still face limited access to timely agricultural information, climate forecasts, and decision-support services. This study examines the role of Artificial Intelligence (AI) in enhancing climate-smart agriculture and knowledge service delivery among smallholder farmers in Kebbi State. The objectives are to assess farmers' awareness and utilization of AI-driven agricultural information systems, and identify constraints to their effective use. The study addresses the knowledge gap regarding the integration of AI technologies in agricultural extension and climate information services in rural farming systems. A mixed-method research design was adopted to selected smallholder farmers. Descriptive statistics was used for analysis. The findings include low digital literacy, poor internet connectivity, limited infrastructure, and inadequate institutional support. The study highlights the need for improved digital extension platforms, farmer training, and policy support to promote AI-enabled advisory services. It concludes that AI has strong potential to strengthen climate-smart decision-making among farmers. The study recommends investment in rural digital infrastructure, capacity building, and collaboration with research institutions, and technology providers to scale AI-based agricultural knowledge services.

Keywords: Artificial Intelligence (AI), Climate-Smart Agriculture (CSA) and Knowledge Service Delivery

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Introduction

Agriculture remains a critical sector in Nigeria's economy, contributing significantly to employment and food security (National Bureau of Statistics, 2022). However, climate change poses severe challenges, including erratic rainfall, drought, and declining soil fertility, which disproportionately affect smallholder farmers (Ayanlade et al., 2018). Climate-Smart Agriculture (CSA) has been promoted as an adaptive strategy to enhance productivity, resilience, and mitigation of greenhouse gas emissions (FAO, 2019). Despite its potential, adoption among smallholder farmers remains low due to limited access to timely and relevant agricultural information (Ogunniyi et al., 2021).

Artificial Intelligence (AI) offers transformative opportunities in agriculture through predictive analytics, weather forecasting, precision farming, and decision-support systems (Oladipo & Akinwale, 2020). AI-driven tools can improve knowledge dissemination and empower farmers with real-time data for informed decision-making. In Kebbi State, where agriculture is predominantly rain-fed, integrating AI into extension services could significantly improve CSA adoption. However, empirical evidence on AI utilization among smallholder farmers remains limited.

Problem Statement

Despite increasing awareness of CSA practices, smallholder farmers in Kebbi State continue to experience low productivity due to inadequate access to reliable agricultural information and climate forecasts. Traditional extension services are often insufficient, understaffed, and unable to meet farmers' needs (Abdullahi et al., 2020).

Although AI technologies have the potential to bridge this gap, their adoption in rural Nigeria is still at a nascent stage. There is limited empirical data on farmers' awareness, usage, and constraints regarding AI-driven agricultural services. This gap necessitates an investigation into how AI can enhance CSA and knowledge delivery. The main objective is to examine the role of AI in enhancing climate-smart agriculture among smallholder farmers in Kebbi State. Specific objectives are to:

1. Assess farmers' awareness of AI-driven agricultural information systems.
2. Determine the level of utilization of AI technologies in farming activities.
3. Identify constraints to the adoption of AI in climate-smart agriculture.

Concept of Climate-Smart Agriculture (CSA)

Climate-Smart Agriculture (CSA) is an integrated approach aimed at transforming agricultural systems to support food security under changing climatic conditions. According to the Food and Agriculture Organization, CSA is built on three interrelated pillars: (i) sustainably increasing agricultural productivity and incomes, (ii) enhancing resilience and adaptation to climate change, and (iii) reducing or removing greenhouse gas emissions where possible. In Nigeria, CSA practices include the use of drought-tolerant crop varieties, improved irrigation systems, conservation agriculture, agroforestry, and efficient soil fertility management (Ajayi & Ojo, 2019).

For smallholder farmers in regions such as Kebbi State, CSA is particularly relevant because agriculture is predominantly rain-fed and highly vulnerable to climate variability. Studies by Ayanlade et al. (2018) show that unpredictable rainfall patterns and rising temperatures have already begun to affect crop yields and food security. CSA therefore provides a pathway for farmers to adapt through practices such as climate-resilient seeds, weather-informed planting decisions, and integrated pest management. However, the effectiveness of CSA depends largely on farmers' access to timely and accurate information, which remains a major constraint in rural Nigeria (Ogunniyi et al., 2021).

Artificial Intelligence in Agriculture

Artificial Intelligence (AI) refers to the use of machine learning algorithms, data analytics, and automated systems to perform tasks that typically require human intelligence. In agriculture, AI is increasingly being applied to enhance efficiency, productivity, and sustainability. Applications include yield prediction models, pest and disease detection using image recognition, soil health monitoring, and precision farming techniques (Oladipo & Akinwale, 2020).

AI-powered tools can analyze large datasets such as weather patterns, satellite imagery, and soil conditions to generate actionable insights for farmers. For instance, predictive analytics can help determine optimal planting periods, irrigation schedules, and fertilizer application rates. In the Nigerian context, AI has the potential to address challenges such as low productivity and inefficient resource use by enabling data-driven decision-making.

Despite these benefits, the adoption of AI in agriculture remains limited among smallholder farmers due to infrastructural deficits, low digital literacy, and high costs of technology (Abdullahi et al., 2020). Nonetheless, the growing penetration of mobile phones and digital platforms presents an opportunity to scale AI solutions tailored to local farming systems.

AI and Knowledge Service Delivery

Knowledge service delivery in agriculture refers to the processes through which farmers access information, advisory services, and technical support necessary for improving agricultural practices. Traditionally, this has been achieved through extension services; however, these systems are often overstretched and unable to meet the needs of dispersed rural populations.

AI is revolutionizing knowledge delivery by enabling real-time, personalized, and scalable advisory services. Digital platforms powered by AI such as mobile applications, chatbots, and decision-support systems can provide farmers with instant access to weather forecasts, market prices, pest control recommendations, and best agronomic practices (Aker, 2011). These tools reduce information asymmetry and enhance farmers' capacity to make informed decisions.

In Nigeria, AI-driven agricultural advisory systems are gradually emerging, but their reach remains limited. Ogunniyi et al. (2021) noted that while digital agriculture platforms exist, their effectiveness is constrained by poor internet connectivity and low awareness among farmers. Nonetheless, integrating AI into extension services could significantly improve the dissemination of CSA practices by delivering localized and timely information. This is particularly important for climate adaptation, where decisions must be based on accurate and up-to-date data.

Theoretical Framework: Diffusion of Innovation Theory

This study is anchored on the Diffusion of Innovations theory developed by Everett M. Rogers. The theory explains how new ideas, technologies, or practices spread within a social system over time. It identifies five key stages in the adoption process: knowledge, persuasion, decision, implementation, and confirmation.

According to Rogers (2003), the rate of adoption of an innovation is influenced by its perceived attributes, including relative advantage, compatibility, complexity, trialability, and observability. In the context of this study, AI technologies represent innovations whose adoption among smallholder farmers depends on how beneficial and accessible they are perceived to be.

The theory also categorizes adopters into five groups: innovators, early adopters, early majority, late majority, and laggards. In rural Nigeria, most smallholder farmers fall within the late majority or laggard categories due to limited exposure to new technologies and risk aversion. Factors such as education, access to information, and social networks play a crucial role in influencing adoption decisions.

Applying this theory to AI in climate-smart agriculture, awareness (knowledge stage) is the first critical step. Farmers must first be informed about AI tools and their benefits. This is followed by persuasion, where extension agents and peer networks influence farmers' attitudes toward the technology. The decision to adopt AI is then shaped by factors such as cost, ease of use, and expected benefits. Implementation involves actual use of AI tools in farming activities, while confirmation reinforces continued adoption based on observed outcomes.

The Diffusion of Innovation Theory is particularly relevant because it highlights the importance of communication channels, social systems, and institutional support in technology adoption. It underscores the need for targeted interventions such as training programs, demonstration farms, and digital literacy campaigns to accelerate the adoption of AI technologies among smallholder farmers.

Methodology

The study was conducted in Kebbi State, located in North-Western Nigeria (latitudes 100 8'N to 130 15'N and longitudes 30 30'E to 60 03'E). Agriculture is the primary occupation, characterized by a mix of upland and Fadama (floodplain) farming. The region faces significant climate challenges, including erratic rainfall and desertification, making it a critical site for assessing Climate-Smart Agriculture (CSA) and AI-driven knowledge services. A cross-sectional survey design was adopted. This approach allows for the simultaneous assessment of farmers' current knowledge levels, perceptions of AI, and existing CSA practices.

The target population consists of smallholder farmers across the four agricultural zones of Kebbi State (Birnin Kebbi, Argungu, Yauri, and Zuru). A multi-stage sampling technique was used to select 150 respondents. Primary data was collected using a structured questionnaire to accommodate varying literacy levels (Socio-economic characteristics, AI Awareness and Knowledge Service Delivery). Descriptive statistics (mean, frequency, percentage) and inferential statistics were used for data analysis.

Results and Discussion

Table 1: Socio-Economic Characteristics of Respondents

The findings in Table 1 show that the mean age of farmers was 42.6 years, indicating that respondents are within the economically active age group. This suggests that they possess the physical capacity to adopt new technologies such as AI. This result aligns with Ogunniyi et al. (2021), who reported that the majority of Nigerian smallholder farmers fall within the 40–50 years age bracket.

The average education level of 8.2 years indicates moderate literacy among respondents. This is significant because education enhances the ability to understand and utilize digital technologies. Similarly, Oladipo and Akinwale (2020) found that education significantly improves farmers' capacity to adopt AI-based agricultural tools in Nigeria.

Farm size (2.4 ha) confirms the dominance of smallholder farming systems, which is typical in Northern Nigeria. This finding is consistent with Abdullahi et al. (2020), who reported that most farmers operate on less than 3 hectares. Small farm size often limits access to capital-intensive technologies, which may explain low AI adoption.

Variable	Mean	Std. Dev	Interpretation
Age (years)	42.6	11.3	Active farming population
Education (years)	8.2	4.5	Low–moderate literacy
Farm size (ha)	2.4	1.6	Smallholder dominance
Farming experience (years)	15.8	9.2	Experienced farmers
Annual income (₦)	356,000	120,500	Low-income level

Source: field survey 2026

Table 2: Awareness and Utilization of AI Technologies

Table 2 reveals that only 35.3% of respondents were aware of AI tools, while a mere 24% actually used them. This demonstrates a significant awareness-utilization gap. Such disparity indicates that awareness alone does not guarantee adoption, as other enabling conditions must be met. This finding is consistent with Ogunniyi et al. (2021), who observed that although digital agricultural platforms are increasingly introduced in Nigeria, actual usage remains low due to infrastructural and knowledge constraints (FAO, 2019). The implication is that farmers in Kebbi State are still at the early stages of the innovation adoption curve, corresponding to the "late majority" or "laggards" category in Rogers' Diffusion of Innovation Theory.

Variable	Frequency	Percentage (%)
Aware of AI tools	53	35.3
Not aware	97	64.7
Use AI tools	36	24.0
Do not use	114	76.0

Source: field survey 2026

Table 3: Constraints to AI Adoption

The constraints identified in Table 3 highlight critical barriers to AI adoption. Poor internet access (85.3%) and unreliable power supply (73.3%) emerged as the most severe infrastructural challenges. These findings are strongly supported by Abdullahi et al. (2020), who identified weak rural infrastructure as a major limitation to ICT adoption in Nigerian agriculture.

Low digital literacy (78.0%) and lack of training (65.3%) further emphasize the human capital gap. This agrees with Aker (2011), who stressed that the effectiveness of digital agricultural innovations depends largely on users' technical capacity.

The high cost of devices (70.0%) also indicates economic barriers, particularly among low-income farmers. Compared to studies in developed countries where cost is less prohibitive, this finding highlights the need for subsidies and financial support mechanisms in Nigeria.

Constraint	Frequency	Percentage (%)
Poor internet access	128	85.3
Low digital literacy	117	78.0
High cost of devices	105	70.0
Lack of training	98	65.3
Unreliable power supply	110	73.3

*Multiple Responses
Source: field survey 2026

Table 4: Logistic Regression Results on Determinants of AI Utilization

The regression results in Table 4 provide insights into factors influencing AI adoption. Education (β = 0.145, $p < 0.01$) positively and significantly influences AI usage. This supports the findings of Oladipo and Akinwale (2020), who emphasized that educated farmers are more capable of understanding and applying digital technologies. Internet access (β = 1.215, $p < 0.01$) is the significant predictor of AI utilization. This confirmed by Ogunniyi et al. (2021) found that access to internet services significantly increases the likelihood of adopting digital agricultural tools. Digital literacy (β = 0.894, $p < 0.01$) is also highly significant, reinforcing the importance of technical skills. This aligns with Aker (2011), who highlighted digital competence as a key determinant of ICT adoption in agriculture. Extension access (β = 0.632, $p < 0.05$) and Cooperative membership (β = 0.518, $p < 0.05$) positively influences AI usage, indicating that extension agents play a crucial role in disseminating information about new technologies, sharing and innovation diffusion. This finding corroborates Abdullahi et al. (2020), who emphasized the importance of extension services in technology adoption.

Income (β positive, $p < 0.05$) indicates that wealthier farmers are more likely to adopt AI technologies, likely due to affordability. This agrees with Ajayi and Ojo (2019), who found that financial capacity is a key determinant of adopting improved agricultural practices.

Age shows a negative relationship (β = -0.021), implying that younger farmers are more inclined toward AI adoption. This supports earlier findings by Aker (2011). Farm size and farming experience, however, were not statistically significant, suggesting that technological adoption is more influenced by access to information and resources than by scale of operation.

Variable	Coefficient (β)	Std. Error	z-value	Significance
Constant	-2.315	0.845	-2.74	**0.006**
Age	-0.021	0.011	-1.91	*0.056*
Education	0.145	0.052	2.79	**0.005**
Farm size	0.087	0.064	1.36	0.174
Farming experience	-0.012	0.010	-1.20	0.230
Extension access	0.632	0.280	2.26	**0.024**
Internet access	1.215	0.350	3.47	**0.001**
Digital literacy	0.894	0.210	4.26	**0.000**
Cooperative membership	0.518	0.245	2.11	**0.035**
Income	0.000003	0.000001	2.50	**0.012**

Source: field survey 2026

Conclusion

The study concludes that although Artificial Intelligence (AI) holds strong potential for enhancing climate-smart agriculture (CSA) and improving knowledge service delivery among smallholder farmers in Kebbi State, its adoption remains low due to limited awareness, poor digital literacy, and inadequate infrastructure. The results further reveal that factors such as education, internet access, digital literacy, extension services, and income significantly influence AI utilization, while major constraints include poor connectivity, high cost of devices, and unreliable power supply. This indicates that AI-driven agricultural transformation is still at an early stage and requires supportive systems to scale effectively.

Recommendations:

1. Government and stakeholders should invest in rural digital infrastructure, particularly internet connectivity and electricity supply.
2. Capacity-building programs should be implemented to improve farmers' digital literacy and awareness of AI tools.
3. Extension services should integrate AI-based advisory platforms to enhance timely and location-specific agricultural information delivery.

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