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Use of Generative AI by Small-scale Farmers in Nigeria: An Empirical Study

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HIGHLIGHTS

- Majority of the farmers demonstrated digital access
- More than half of the farmers had used generative AI, mostly for information access and basic research about their farm operations
- Educational attainment significantly enhances AI awareness

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ABSTRACT

The study, conducted in 2025, investigated the digital readiness and use of generative artificial intelligence (AI) among small-scale farmers in Nigeria. A multi-stage sampling technique was used to select 120 small-scale farmers, and data were collected through interview schedules. The majority (62.5%) were small-scale farmers with over ten years of farming experience. Many of the small-scale farmers had digital access as a lot of them owned smart phones (64.2%) had internet connectivity (65%), and regularly used the internet (53.3%). Traditional media (Radio and TV) (63.3%) remained their primary source of agricultural information. Extension service access (4.2%) was notably low. Many small-scale farmers (64.2%) had used generative AI, mainly for accessing information (45%) and conducting basic research about their farm operations and general well-being (17.5%), and most indicated willingness to continue its use (89.2%). However, major barriers to the use of generative AI included limited awareness and lack of access to digital devices. AI awareness was generally low but positively associated with education. Although generative AI adoption is growing, significant challenges remain, underscoring the need for targeted generative AI training in agriculture as well as the design and implementation of more generative AI awareness program.

INTRODUCTION

Agriculture remains the backbone of rural economies in Africa, especially Nigeria where farming is a significant source of livelihood and food security. However, the productivity and sustainability of farming are undermined by several challenges, including limited access to reliable agricultural information. The traditional extension system inability to deliver localized and adaptive agricultural information is a significant bottleneck in improving farming practices

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and productivity in the developing economy. Therefore, rapid evolutions of artificial intelligence (AI) technologies, which have steered a wave of potential in different area of development, have also become a game changer in solving the limitation of Agricultural Extension for sustainable agriculture and rural development. Among these technologies, Generative Artificial Intelligence (Generative AI) stands out for its ability to create new, original content such as text, images, audio, and even video by learning from existing datasets (Bommasani et al., 2021).

Unlike traditional AI systems that rely on predefined rules and outputs, generative AI models, powered by architectures like Generative Adversarial Networks (GANs), transformers, and diffusion models are capable of generating novel and contextually relevant outputs, often mimicking human creativity (Goodfellow et al., 2014; Vaswani et al., 2017). Generative AI offers unprecedented potential to bridge the longstanding gaps in extension services, market intelligence, and farmer education. Nigeria faces a chronic shortage of agricultural extension agents, with the ratio of farmers to extension agents standing at approximately 1:10,000 in some regions (FMARD, 2023). This shortage limits farmers' access to timely, personalized information on crop management, pest control, weather forecasting, and market pricing. By leveraging generative AI tools such as ChatGPT and other language models, farmers can now obtain instant, tailored advice in multiple languages thereby facilitating a form of digital extension service (Sarfo et al., 2025). Moreover, generative AI supports low-literate or semi-literate farmers through the integration of voice-based assistants and localized language generation, enabling interaction in native tongues without requiring formal literacy (FAO, 2021). For example, applications such as Google's voice search and AI-enabled WhatsApp chatbots are increasingly being deployed in agricultural value chains to support farmer queries. Generative AI also enhances decision-making by analyzing patterns in historical farm data, weather trends, and pest outbreaks to generate early warnings and predictive insights (Shahriar, 2025). Despite these benefits, challenges such as digital illiteracy, unreliable internet connectivity, and limited access to AI-capable devices, and data privacy concerns continue to hinder widespread adoption, particularly among smallholder farmers (Ogwuegbu & Ajobiewe, 2025). This study, therefore, explores digital readiness, and awareness levels of farmers in Nigeria concerning generative AI. Understanding these factors is essential for scaling AI-enabled solutions in agriculture and ensuring that innovations like generative AI do not exacerbate existing inequalities but instead serve as catalysts for rural transformation and food security.

METHODOLOGY

The study adopted a quantitative survey design to assess the use of generative artificial intelligence (AI) as a source of agricultural information among farmers in Nigeria. Ekiti State was purposively selected due to its agricultural prominence and the increasing challenges associated with access to reliable, timely agricultural information. The population of the study comprised small-scale farmers across the 16 Local Government Areas (LGAs) of Ekiti State. A multistage procedure was employed to select the small-scale farmers. At the first stage, two LGAs, Irepodun/ Ifelodun and Gbonyin were purposively selected based on Agricultural production relevance in Ekiti State. At the second stage, two communities were purposively selected from each LGA based on their unique farming and cropping system, such as Rice, Maize, Yam cropping system and Livestock farming. Based on this criterion, Igbemo Ekiti and Afao Ekiti from Irepodun/ Ifelodun LGA and Ijan Ekiti and Iluomoba Ekiti from Gbonyin LGA were selected. At the final stage, thirty (30) farmers were randomly selected from these four communities, yielding a total sample size of 120.

The Primary data were collected using an interview schedule. The questionnaire was developed and reviewed by the Software Engineers specialized in Generative AI as well as Agricultural Extension experts. The sections included are the socio-economic characteristics, awareness and use of generative AI, and its perceived impact on farming decisions. To accommodate varying literacy levels, questions were translated into Yoruba during interviews where needed. Descriptive statistics such as frequency, percentage, mean were used to summarize the socio-demographic data and levels of awareness and use of AI tools. Inferential statistics, particularly Chi Square test was used to understand the relationship between farmers' level of Education and AI awareness. SPSS was used to analyze the data. Hypotheses were tested at a 5% significance level ($p \leq 0.05$).

RESULTS

The results of demographics, Digital access and ICT usage of small-scale farmers in the study area were presented in Table 1. The socio-economic characteristics of respondents revealed a farming population dominated by middle-aged adults, with 68.4 per cent between 31 and 50 years, a period typically associated with high productivity and openness to innovation (FAO, 2020). Farming was overwhelmingly male-dominated (92.5%), reflecting structural gender imbalances in land access and decision-making (Doss, 2018). Educational attainment was relatively favorable as 79.1% had at least secondary education, a factor positively correlated with the adoption of improved technologies and management practices (World Bank, 2019). Farm structure reflected smallholder dominance, with 45.0% cultivating between one and five acres, consistent with regional patterns where smallholders provide over 80% of agricultural output yet face challenges in scaling (HLPE, 2013). Against this backdrop, digital readiness emerges as both promising and uneven. Smartphone ownership (64.2%) and internet access (65.0%) indicate considerable opportunity for digital agricultural transformation, aligning with evidence that mobile phones are the leading ICT tool in African farming systems (Aker & Mbiti, 2010). Comparable findings in rural India confirm this global trend (Anand et al., 2022). However, the 35.8% relying on basic phones and 34.2% without internet reflect a persistent digital divide. Traditional channels remain significant as 60.0% relied on radio for agricultural information compared to 4.2% for extension agents as presented in Table 2, underscoring that digital innovation must complement and not replace established communication modes (Omotayo, 2005; Lwoga, 2010). However, the growing role of the internet (16.7%) and social media (15.8%) indicates that digital channels are gaining ground, especially among tech-savvy farmers.

Table 1. Small-scale farmers' Demographics, Digital access and ICT usage

Characteristics	Items	Percentage
Farm Size	Small-scale dominance	1–5 acres: 45.0; 6–10 acres: 17.5; >10 acres: 10.0
Type of Device	Smartphone	64.2
	Basic Mobile Phone	35.8
Internet Access	Yes	65.0
	No	35.0
Internet Usage Hours	No Internet Access	34.2
	Less than 1 hour	10.0
	1–3 hours	18.3
	4–6 hours	16.7
	More than 6 hours	20.8
Internet Frequency of Use	No Internet Access	34.2
	Regularly	53.3
	Sometimes	12.5

Table 2. Small-scale farmers' Agricultural information sources

Information Source	Percentage
Extension Agents	4.2
Radio	60.0
TV	3.3
Internet including Generative AI	16.7
Social Media	15.8

The finding as presented in Table 3 was the moderately high usage of generative AI tools (64.2%) among the small-scale farmers. This is impressive considering that the adoption of emerging technologies in rural settings is often low due to infrastructural and educational constraints. The primary purposes of use information access (45.0%) and research (17.5%) underscore the value of generative AI as an advisory and knowledge tool, rather than for direct mechanization. This is consistent with Mittal and Mehar (2016), reported that ICT tools significantly improve access to farm-related information, contributing to productivity enhancement. Das et al. (2024) also reported the same results in their study on ChatGPT as AI-enabled Assistant for Agriculture stakeholders in India. However, despite this high level of usage, 22.5% of non-users indicated lack of awareness as a barrier, followed by 13.3% who lacked smart phones. This shows that both informational and material access barriers continue to hinder the widespread adoption of AI technologies. As Adesina (2015) pointed out, access to devices and exposure to innovations are strong predictors of ICT tool adoption in agriculture. Encouragingly, the willingness to continue using generative AI was high (89.2%), suggesting strong future potential if barriers are addressed. Motivations for continued usage for basic research about their farm operations (41.7%), information (29.2%), and training (17.5%) indicate that farmers are seeking tools that can support evidence-based decision-making and learning. This corroborates Aker and Ksoll's (2012) assertion that digital tools empower farmers by providing timely and relevant information, thereby enhancing decision-making and resilience. The shifting trajectory of traditional Agricultural Extension to Digital Agricultural Extension system which was made possible through the advent of Mobile phone globally, has been a platform for adoption of Generative AI to thrive, especially in rural areas (Adenubi et al., 2021).

Table 3. Small-scale farmers' Generative AI usage and continuous willingness to use

Variable	Items	Percentage
Use of Generative AI	Yes	64.2
	No	35.8
Purpose of Use	For Information	45.0
	For basic Research about farm operations	17.5
	For Fertilizer Application	1.7
Reason for no usage	Not Aware of Generative AI	22.5
	Lack of Smartphone	13.3
Willingness to continue Use AI	Yes	89.2
	No	10.8
Motivation for continuous usage	Research	41.7
	Information Source	29.2
	Training	17.5
	Farming Methods	0.8
	Not Willing to Use	10.8

One of the most significant findings of this study was the strong positive correlation between educational level and awareness of artificial intelligence (Table 4). The Chi-Square test confirmed a statistically significant association ($\chi^2 = 45.965$, $p < 0.001$), with awareness increasing progressively with higher education (Table 5). Small-scale farmers with tertiary education demonstrated the highest awareness levels (48.4% high, 32.3% moderate), while those with no or only primary education had nearly 100% low awareness. This pattern highlights the role of education in shaping not only knowledge but also digital behavior. Educated farmers are more likely to explore and use AI-based tools because they can better comprehend technological features and evaluate their benefits. Kolapo and Didunyemi (2024) similarly found that educated farmers were more likely to adopt digital innovations and integrate them into their farming practices. The linear association value of 30.922 also suggests a strong positive trend: as education increases, so does awareness. This has significant implications for agricultural policy and training programs. To ensure inclusive adoption of digital agriculture, targeted interventions must focus on improving digital literacy among farmers with lower levels of formal education. This may include visual and audio-based training modules, community ICT centers, and peer-to-peer digital coaching programs.

Furthermore, the cross-tabulation (Table 4) showed that individuals with lower levels of education, particularly those with

Table 4. Cross-tabulation of Small-scale farmers' education level and awareness of Generative AI

Education Level	Low Awareness	Moderate Awareness	High Awareness	Total
No Formal Education	94.1	5.9	0	14.2
Primary Education	100	0	0	6.7
Secondary Education	71.9	20.3	7.8	53.3
Tertiary Education	19.4	32.3	48.4	25.8

Table 5. Chi-Square test results

Test	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	45.965	6	.000
Likelihood Ratio	49.312	6	.000
Linear-by-Linear Association	30.922	1	.000
Number of Valid Cases	120		

no formal or only primary education, tended to exhibit very low levels of awareness about AI. For instance, 100% of those with only primary education and 94.1% of those with no formal education fell into the low awareness category. In contrast, a substantial portion of small-scale farmers with tertiary education demonstrated high awareness (48.4%) or at least moderate awareness (32.3%), indicating a strong association between higher educational attainment and increased AI awareness. This trend was further supported by the Chi-Square test in Table 5, where the Pearson Chi-Square value was 45.965 with a p-value of less than 0.001, confirming that the observed association is statistically significant and not due to chance. The Linear-by-Linear Association value of 30.922 ($p < 0.001$) also indicates a positive linear trend, meaning that awareness of AI increases steadily with higher levels of education. Although a small portion of the data (33.3%) included expected counts below 5, the minimum expected count remained above 1.0, suggesting the test remains robust. These findings suggest that education plays a critical role in shaping public understanding and awareness of AI. Therefore, efforts to increase AI awareness should prioritize educational outreach, especially to those with lower levels of formal schooling, to bridge the knowledge gap and promote inclusive technological literacy. This finding support Chaturvedi and Vatta (2025), who found that education can increase the awareness as well as the use of digital technology farming practices.

DISCUSSION

The unevenness in digital access, internet use, and AI awareness observed in this study reflects the broader digital divide in rural Nigeria. While some farmers are fully engaged with digital tools and AI platforms, others remain disconnected due to infrastructural, economic, or educational constraints. Bridging this divide will require concerted efforts from multiple stakeholders, government, private sector, NGOs, and academic institutions. Firstly, infrastructure such as reliable internet and electricity must be expanded to underserved areas. Secondly, affordable digital devices, particularly smart phones, should be made available through subsidized schemes or community ownership models. Thirdly, digital literacy initiatives tailored to the rural context are essential. These must be localized, accessible in native languages, and practical in their approach. Importantly, extension services must be re-imagined to incorporate digital tools like generative AI. Extension agents can act as digital intermediaries, demonstrating AI tools and assisting farmers in their usage. This integrated approach, combining human and digital channels, will ensure broader reach and deeper engagement.

CONCLUSION

The study highlights the critical socio-economic and digital factors influencing farmers' participation in agricultural innovation and AI adoption. The findings revealed that majority of Small-scale farmers in the study area are digitally ready for the adoption of generative AI. However, limited internet access in the rural area, poor electricity to charge a Smartphone, gender disparity in on-farm activities, digital divide, low level of awareness of Generative AI, constitute a major barrier to the adoption of Generative AI by small-scale farmers in the rural areas. Notably, the high level of smart phone ownership and willingness to use generative AI tools indicates strong potential for digital transformation in agriculture. Furthermore, the significant relationship between education level and AI awareness underscores the importance of targeted educational interventions. To fully leverage technology for agricultural growth, policy efforts should prioritize digital literacy, infrastructure development, and inclusive access to extension services and AI-based tools.

DECLARATIONS

Ethics approval and informed consent: Informed consent was sought from the respondents during the course of the research.

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The authors declare that during the preparation of this work, thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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