Artificial Intelligence Applications for Precision Agriculture: Opportunities, Challenges, and Prospects for Smallholder Farmers in Adamawa State, Nigeria

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Abstract
Precision agriculture represents a paradigm shift in agricultural production, leveraging digital technologies to optimize inputs, enhance yields, and minimize environmental impact. While Artificial Intelligence (AI) has demonstrated transformative potential in advanced agricultural systems worldwide, its adoption among smallholder farmers in Northern Nigeria remains largely underexplored. This study investigates the opportunities, challenges, and prospects of AI applications for precision agriculture among smallholder farmers in Adamawa State, Nigeria. Employing a descriptive survey research design, data were collected from 120 farmers across six local government areas using structured questionnaires and semi-structured interviews. Findings indicate that while 82.5% of farmers expressed strong interest in AI-driven agricultural solutions, actual adoption remains minimal. Key perceived benefits included improved crop yield (M = 4.28), reduced input waste (M = 4.15), and enhanced pest and disease detection (M = 4.09). Major barriers included limited digital literacy (90.8%), high cost of smart devices and data services (87.5%), erratic power supply (85.0%), and limited or no access to internet

connectivity (83.3%). The study concludes that AI offers substantial potential for transforming agricultural productivity in Adamawa State, but meaningful adoption requires more than technology transfer. It demands context-appropriate infrastructure development, localized AI solutions, farmer-centric capacity building, and supportive institutional frameworks. Evidence-based recommendations are proposed for policymakers, agricultural extension services, and technology developers to facilitate equitable and sustainable AI integration in smallholder agricultural systems.

Keywords: *Artificial Intelligence, Precision Agriculture, Smallholder Farmers, Digital Divide, Agricultural Transformation, Adamawa State, Sustainable Development*

1. Introduction

1.1 Background to the Study

Agriculture remains the backbone of Nigeria's economy, employing over 70% of the rural workforce and providing livelihoods for millions of households (National Bureau of Statistics [NBS], 2024). In Northern Nigeria, including Adamawa State, smallholder farmers constitute the vast majority of agricultural producers, operating on less than two hectares on average and relying largely on traditional methods and manual labour (United Nations Development Programme [UNDP], 2023). Despite their central role in food security and economic development, these farmers face persistent challenges: low productivity, erratic rainfall patterns linked to climate change, soil degradation, pest and disease outbreaks, and limited access to timely information and improved technologies (Essien et al., 2024). Precision agriculture is often described as "farming with information"—it uses digital technologies to observe, measure, and respond to variability in crop and field conditions. Artificial Intelligence, in particular, has emerged as a transformative enabler of precision agriculture, offering capabilities that include yield prediction, disease detection, soil analysis, weather forecasting, and automated resource management (Kamilaris & Prenafeta-Boldú, 2018). From machine learning models that analyse satellite imagery to identify crop stress, to mobile applications that provide personalized advisory services, AI holds the potential to address many of the constraints that limit smallholder productivity (World Bank, 2025). Yet the global conversation around AI in agriculture often overlooks the realities of resource-constrained contexts. While high-tech farms in advanced economies adopt autonomous machinery and drone-based monitoring, most smallholder farmers in Adamawa State lack reliable electricity, consistent internet access, and even basic digital literacy (Essien et al., 2024). The promise of AI-driven agriculture risks widening rather than narrowing the gap between resource-rich and resource-poor producers unless it is designed, adapted, and deployed with local realities at its core. This study responds to that need by examining the actual conditions, perceptions, and experiences of smallholder farmers in Adamawa State as they stand at the threshold of the AI era.

1.2 Statement of the Problem

The potential of Artificial Intelligence to revolutionize agricultural practice is well documented in global literature. However, the transfer of these technologies to smallholder communities in Northern Nigeria cannot be assumed to be straightforward. There exists a significant gap between the technological capabilities available in principle and the lived realities of farmers who operate with limited infrastructure, low digital literacy, and constrained financial resources. While several studies have examined general technology adoption in Nigerian agriculture, there

is limited empirical evidence specifically focused on AI perceptions, awareness, and constraints among smallholder farmers in Adamawa State. Without this understanding, interventions risk being irrelevant, inaccessible, or unsustainable. This study addresses that gap by providing empirical insights into the opportunities, challenges, and prospects of AI applications for precision agriculture in Adamawa State, Nigeria.

1.3 Research Questions

- What is the level of awareness and perception of Artificial Intelligence and precision agriculture technologies among smallholder farmers in Adamawa State?
- What potential benefits of AI-driven precision agriculture are recognized by smallholder farmers?
- What are the primary barriers limiting the adoption of AI applications among smallholder? farmers in the study area?
- What strategies can facilitate the equitable and sustainable integration of AI technologies into smallholder agricultural systems in Adamawa State?

1.4 Objectives of the Study

- To assess the awareness and perceived benefits of Artificial Intelligence and precision agriculture among smallholder farmers in Adamawa State.
- To identify the technical, economic, social, and institutional barriers to AI adoption in smallholder agriculture in the study area.
- To propose context-appropriate strategies and recommendations for advancing AI-enabled precision agriculture in Adamawa State, Northern Nigeria.

2. Literature Review

2.1 Conceptual Framework

2.1.1 Precision Agriculture and Artificial Intelligence

Precision agriculture is an integrated farm management concept that aims to optimize returns on inputs while preserving resources. It is built on the principle that agricultural fields are not uniform, and that management practices should therefore be tailored to specific conditions within each field (Zhang et al., 2002). Where traditional agriculture applies uniform treatments across an entire field, precision agriculture seeks to apply the right treatment, at the right place, and at the right time. Artificial Intelligence serves as the analytical engine that makes large-scale precision agriculture practical. Through machine learning, computer vision, and predictive analytics, AI systems can process vast volumes of data—from satellite imagery, soil sensors, weather stations, and historical yield records—to generate actionable insights that would be impossible to derive manually (Ajith & Vijayakumar, 2025). In agricultural contexts, AI applications are commonly grouped into five categories: crop health monitoring and disease detection, yield prediction and optimization, soil analysis and fertility management, irrigation and water resource management, and pest and weed identification (Khan et al., 2024).

2.1.2 Smallholder Agriculture in Northern Nigeria

Smallholder agriculture is not merely an economic activity in Northern Nigeria; it is a way of life, a cultural practice, and the primary source of household food security. Most farms are family-operated, relying on household labour and traditional knowledge passed down through generations (International Food Policy Research Institute [IFPRI], 2023). Agricultural practices

are strongly influenced by climate, with the rainy season determining planting and harvesting cycles. Over the past two decades, changing rainfall patterns, prolonged dry spells, and increasing temperatures have placed significant stress on farming systems, making traditional climate knowledge less reliable (Ahmadu et al., 2024).

2.2 Empirical Review

Recent scholarship on AI in agriculture reveals a striking divide between global possibilities and local realities. Kamilaris and Prenafeta-Boldú (2018), in a comprehensive global review, found that while AI applications in agriculture have grown exponentially since 2010, less than 8% of documented deployments are in low-income countries. In the Nigerian context, AGRA (2026) noted that digital agricultural interventions remain concentrated in urban and peri-urban areas, with rural communities—where most smallholders reside—being largely excluded. Similarly, Essien et al. (2024) identified infrastructure deficits, cost, and literacy gaps as the primary triad of barriers limiting equitable digital access. These findings suggest that AI adoption is not simply a matter of providing technology; it requires addressing foundational inequalities in access, capacity, and infrastructure.

2.3 Theoretical Framework

This study is anchored on the Unified Theory of Acceptance and Use of Technology (UTAUT2), extended to include contextual constraints. Developed by Venkatesh et al. (2012), UTAUT2 posits that technology adoption is influenced by performance expectancy, effort expectancy, social influence, facilitating conditions, price value, and habits. While the model has been widely validated, its application in low-resource contexts requires explicit attention to structural barriers such as electricity, internet connectivity, and affordability that are often assumed away in studies conducted in high-income settings. This study therefore interprets UTAUT2 through the lens of the Digital Divide Framework, which emphasizes that technology access is shaped not only by individual choice but also by broader social, economic, and infrastructure realities (van Dijk, 2024).

3. Methodology

3.1 Research Design

This study employed a descriptive survey research design, which is appropriate for examining the characteristics, perceptions, and conditions of a defined population without manipulating variables (Creswell, 2014). The design was selected because it allows for the systematic collection of data on farmers' awareness, attitudes, perceived benefits, and experienced challenges regarding AI-driven precision agriculture.

3.2 Study Area

The study was conducted in Adamawa State, located in the North-East geopolitical zone of Nigeria. Adamawa State has a projected population of approximately 4.9 million people as of 2026 (Adamawa State Government, 2026; Nigerian Informer, 2026), with agriculture serving as the primary economic activity. The state has significant agricultural potential, producing crops including maize, sorghum, millet, rice, groundnuts, soybeans, and cotton. Six Local Government Areas were purposively selected: Yola South, Hong, Maiha, Ganye, Numan, and Mubi South. These areas represent both urban-influenced and rural agricultural communities, ensuring a diversity of perspectives.

3.3 Population and Sampling

The target population comprised smallholder farmers defined as those cultivating two hectares or less who were actively engaged in farming during the 2025/2026 agricultural season. A multi-stage sampling technique was employed. First, three farming communities were selected from each of the six Local Government Areas. Second, ten farmers were randomly selected from each community, yielding a total sample of 180 farmers. Of these, 145 questionnaires were returned, representing a response rate of 80.6%, and 120 were found to be valid and complete for analysis. This sample size is consistent with recommendations for descriptive survey research in agricultural contexts, which typically require a minimum of 100 participants for reliable descriptive inference (Israel, 2023).

3.4 Instrumentation

Data were collected using two complementary instruments: a structured questionnaire and a semi-structured interview guide. The questionnaire was developed after an extensive review of related literature and was organized into five sections: Section A: Demographic and farming characteristics; Section B: Awareness and current use of digital technologies; Section C: Perceived benefits of AI-driven precision agriculture; Section D: Barriers and challenges to adoption; Section E: Suggestions and recommendations.

All items in Sections C and D were measured on a 5-point Likert scale: 5 = Strongly Agree, 4 = Agree, 3 = Undecided, 2 = Disagree, 1 = Strongly Disagree. A criterion mean of 3.00 was established, with values above 3.00 indicating agreement or perceived importance of the item. For this study, digital literacy was operationalized as the ability to access, understand, and use digital technologies (including mobile phones and internet-based tools) for agricultural purposes; this construct was measured through multiple survey items and supplemented by qualitative interview data to capture its breadth. The semi-structured interview guide explored deeper perspectives, including farmers' understanding of technology, sources of agricultural information, and practical suggestions for making new technologies accessible. Fifteen farmers were purposively selected for interviews to ensure representation across gender, age, and farming experience.

3.5 Validity and Reliability

The questionnaire was subjected to face and content validation by three experts: two agricultural extension specialists and one computer science educator. Each item was assessed for clarity, cultural appropriateness, and alignment with the research objectives. Suggestions for rewording and simplification were incorporated before final administration. To ensure linguistic and conceptual validity across languages, the questionnaire was initially developed in English, then translated into Hausa and Fulfulde by two bilingual agricultural extension specialists. A back-translation into English was conducted by an independent translator; minor discrepancies were resolved through discussion with the research team. A pilot study was conducted with 20 farmers who were not part of the final sample. Cronbach's alpha coefficient was calculated to measure internal consistency, yielding an overall value of $\alpha = 0.82$, which indicates good reliability (Nunnally, 1978). Subscale reliabilities were computed for the perceived benefits ($\alpha = 0.84$) and barriers ($\alpha = 0.76$) subscales, both exceeding the commonly accepted threshold of 0.70.

3.6 Ethical Considerations

The study adhered to established ethical standards. Permission was sought from community

leaders and agricultural extension officers before approaching farmers. Informed consent was obtained from all participants, who were assured that participation was entirely voluntary, that they could withdraw at any time, and that all information provided would remain confidential and used solely for research purposes. No personal identifiers were included in the final analysis.

3.7 Data Collection Procedure

Data were collected between June and July 2026. Given the low literacy levels among some farmers, the questionnaires were administered through face-to-face interviews in the local Hausa and Fulfulde languages, with researchers reading each item aloud and recording responses. This approach ensured that all eligible farmers, regardless of formal education level, could participate. Each session lasted approximately 20–30 minutes. The semi-structured interviews were conducted in a conversational manner, audio-recorded with consent, and transcribed verbatim.

3.8 Data Analysis

Quantitative data were analyzed using IBM SPSS Statistics Version 26. Descriptive statistics, frequency, percentage, mean, and standard deviation were computed for all variables. Qualitative data from interviews were analysed using thematic analysis following Braun and Clarke's (2006) six-phase framework: familiarization with the data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report. To enhance trustworthiness, 20% of transcripts were double-coded by a second researcher, yielding an inter-coder reliability coefficient of 0.88 (Cohen's kappa). Member checking was conducted with five interview participants to confirm the accuracy of identified themes.

4. Results and Findings

4.1 Demographic and Farming Characteristics

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	75	62.5
	Female	45	37.5
Age Group	Below 30	12	10.0
	30–45	58	48.3
	46–60	41	34.2
	Above 60	9	7.5
Years of Farming Experience	Less than 5 years	15	12.5
	5–15 years	48	40.0
	16–30 years	45	37.5
	Above 30 years	12	10.0
Farm Size	Less than 1 hectare	52	43.3
	1–2 hectares	68	56.7
Primary Source of Information	Fellow farmers	78	65.0
	Extension officers	25	20.8
	Radio	14	11.7
	Mobile phone/internet	3	2.5

Ownership of Mobile Phone	Yes	87	72.5
	No	33	27.5
Access to Electricity	Daily	12	10.0
	Occasionally	45	37.5
	Rarely/Never	63	52.5

Table 1. Demographic and Farming Profile of Respondents (N = 120)

The sample was predominantly male (62.5%), reflecting the gender dynamics of farming in the region. Most farmers were between 30 and 60 years old, with significant farming experience—over 87.5% had five or more years of experience. Farm sizes were uniformly small, with all respondents cultivating two hectares or less. Mobile phone ownership stood at 72.5%, yet only 2.5% cited mobile phones as a primary source of agricultural information. Access to electricity was a major challenge, with 52.5% reporting rarely or never having access. Fellow farmers remained the dominant source of agricultural information, indicating strong social knowledge networks but limited digital information flow.

4.2 Awareness and Perceived Benefits of AI-Driven Precision Agriculture

Perceived Benefit	Mean	Std. Dev.	Rank	Interpretation
AI can help increase crop yield	4.28	0.81	1	Agree
AI can reduce waste of seeds and fertilizer	4.15	0.85	2	Agree
AI can help detect diseases and pests early	4.09	0.89	3	Agree
AI can improve water use efficiency	3.98	0.92	4	Agree
AI can provide better weather forecasts	3.95	0.90	5	Agree
AI can reduce the time spent on farm activities	3.88	0.95	6	Agree
Overall Mean	4.06	—	—	Agree

Table 2. Perceived Benefits of AI-Driven Precision Agriculture

When the concept was explained in simple, local terms, farmers expressed remarkably positive perceptions of AI's potential. The highest-rated benefit was increased crop yield (M = 4.28), followed by reduced input waste and early disease detection. All items scored well above the 3.00 criterion, indicating strong agreement across all potential benefits. This suggests that the barrier to adoption is not a lack of interest or perceived value, but rather other constraints.

4.3 Barriers to AI Adoption

Barrier	Percentage Reporting as Major Constraint	Rank
I do not know how to use these technologies	90.8	1
Smartphones and data are too expensive	87.5	2
There is no steady electricity to charge devices	85.0	3
Internet connection is not available in my area	83.3	4
I do not understand English well enough	70.0	5
I do not see anyone using these technologies around me	65.8	6
I am not sure if these technologies actually work	58.3	7
I am afraid of making mistakes with new technology	52.5	8

Table 3. Barriers to AI Adoption among Smallholder Farmers in Adamawa State

The findings reveal a clear hierarchy of constraints. Digital literacy—measured as the ability to use and understand digital technologies for agricultural purposes—emerged as the single greatest barrier (90.8%), followed closely by cost (87.5%), electricity (85.0%), and internet access (83.3%). Language, lack of visible examples, and uncertainty also contributed. These barriers are not independent: limited electricity limits phone use; limited internet limits what phones can do; limited literacy limits even basic operation.

4.4 Qualitative Findings

Three core themes emerged from the interviews:

- **Theme 1**: Interest without Access: "We hear that there are machines that can tell you when to plant and when to water. We want these things. But where do we get them? How do we operate them? We have the desire, but we do not have the means." (Male farmer, 49 years, translated from Hausa)
- **Theme 2:** The Language and Knowledge Gap: "Many of these things are written in English. We speak Hausa and Fulfulde. Even if I have the phone, if I cannot read what it says, it is just a heavy stone in my pocket." (Female farmer, 44 years, translated from Hausa)
- **Theme 3**: Need for Demonstration and Trust: "Show us one person who is using it and getting better harvest. Once we see it working with our own eyes, we will accept it. But we cannot just believe words." (Male farmer, 57 years, translated from Hausa)

5. Discussion

5.1 Awareness, Interest, and the Potential of AI

The study reveals a striking paradox: farmers overwhelmingly recognize the potential benefits of

AI-driven precision agriculture, yet actual adoption remains effectively zero. The consistently high mean scores across all benefit categories, particularly improved yield, reduced waste, and early disease detection, indicate that when the concept is explained in accessible, practical terms, farmers understand and value its potential. This finding contradicts the common assumption that resistance to new technology stems from conservatism or lack of interest. Instead, it aligns with recent studies by AGRA (2026) and Essien et al. (2024), who found that Nigerian farmers are often highly receptive to innovation when it is relevant to their needs. The challenge is not convincing farmers of the value of technology; it is making that technology accessible, affordable, and usable.

5.2 The Layered Barriers to Adoption

The barriers identified in this study form a mutually reinforcing system. As shown in Table 3, 90.8% of farmers reported not knowing how to use these technologies, making digital literacy the single greatest barrier—higher than cost (87.5%) or electricity access (85.0%). At the most fundamental level is infrastructure: without reliable electricity (reported as a major constraint by 85.0%) and internet connectivity (83.3%), digital technologies cannot function as intended. Above this lies the barrier of cost: even when infrastructure exists, smartphones, data plans, and premium services are often beyond the financial reach of farmers operating on narrow margins. Above cost lies literacy: even when a farmer has a phone and electricity, limited education and digital skills prevent effective use. Language amplifies this gap, as most digital tools are designed for English-speaking users (noted by 70.0% of farmers as a barrier).

These findings extend the UTAUT2 framework by demonstrating that in resource-constrained contexts, facilitating conditions—particularly infrastructure—are not merely background factors but the primary determinants of adoption. Without them, performance expectancy and effort expectancy become largely theoretical. This supports van Dijk's (2024) Digital Divide Framework, which argues that access to technology occurs across multiple dimensions—motivational, material, skills-based, and usage-based—and that all must be addressed for meaningful inclusion.

5.3 Implications for Practice and Policy

The practical implications of these findings are clear: AI solutions for smallholder farmers in Adamawa State cannot simply be transferred from developed contexts. They must be designed from the ground up with local realities in mind. This means tools that function offline, operate on basic mobile phones, use local languages, and rely on voice rather than text-based interaction. It means interventions that combine technology with training, infrastructure investment, and financial support. For extension services, the findings suggest a critical new role: agricultural extension officers must evolve into digital extension officers, bridging the gap between emerging technologies and farming communities. Partnerships between computer scientists, agricultural experts, and local communities are essential to ensure that AI solutions are not just technically advanced but socially and culturally appropriate.

5.4 Limitations of the Study

This study has several limitations. First, the data relied on farmers' self-reported perceptions, which may be subject to social desirability bias, with participants potentially overstating their interest in new technologies to align with researcher expectations. Second, the sample was limited to six Local Government Areas in Adamawa State, and findings may not be generalizable

to all regions of Northern Nigeria or the country as a whole. Third, the study employed a cross-sectional design, capturing perceptions at a single point in time; this design cannot establish causal relationships between identified barriers and adoption behavior, and longitudinal research would be valuable in tracking how awareness and attitudes evolve as technologies become more visible. Fourth, while digital literacy was operationalized broadly and supplemented with qualitative data, the primary barrier item focused on foundational operational ability, which may not capture the full breadth of skills, knowledge, and access that constitute the construct. Finally, while the study identified barriers, it did not test specific interventions—this remains an important area for future research.

6. Conclusion and Recommendations

6.1 Conclusion

Artificial Intelligence holds genuine promise for transforming smallholder agriculture in Adamawa State, Northern Nigeria. The farmers in this study demonstrated clear interest, recognized potential benefits, and expressed willingness to adopt new technologies when those technologies are accessible, understandable, and relevant. However, the path from interest to adoption is blocked by significant, interconnected barriers: limited digital literacy, prohibitive costs, unreliable electricity, absent or expensive internet connectivity, language barriers, and a lack of locally adapted tools. AI-driven precision agriculture will not happen in Adamawa State through market forces alone. It requires deliberate, coordinated action across multiple sectors. It requires education that builds digital competence alongside agricultural knowledge; technology design that respects local languages and contexts; infrastructure that reaches rural communities; and policies that ensure equitable access. The alternative—a future where AI benefits large-scale commercial farmers while leaving smallholders further behind—is both ethically unacceptable and practically unsustainable. The findings of this study suggest that with the right investments and approaches, AI can become a tool for inclusion rather than exclusion, helping to lift productivity, improve food security, and support sustainable development across Adamawa State and similar contexts in Northern Nigeria.

6.2 Recommendations

Based on the findings, the following evidence-based recommendations are proposed, prioritized to align with the study's empirical results (digital literacy identified as the top barrier):

Capacity Building and Extension

- **Integrate Digital Literacy into Extension Services:** Retrain and equip agricultural extension officers to provide digital guidance alongside traditional advice. Extension officers should become the primary bridge between AI tools and farming communities in Adamawa State.
- **Local Language and Voice-Based Tools:** AI agricultural applications must be developed in local languages (Hausa, Fulfulde, etc.) and rely primarily on voice interaction rather than text, to accommodate varying literacy levels.
- **Farmer-to-Farmer Demonstration Programs:** Establish "digital champion" farmers in each community who receive training and then demonstrate technologies to peers. Visible success stories are the most powerful form of promotion.

Technology Design and Development

- **Develop Offline-First, Low-Bandwidth Solutions:** AI tools designed for Adamawa State must function effectively without constant internet access. Satellite-based and locally hosted models should be explored.
- **Co-Design Technologies with Farmers:** Farmers should be involved from the earliest stages of technology development to ensure tools address their actual needs and fit their farming practices.
- **Focus on High-Impact, Simple Applications** First: Begin with accessible use cases—pest identification, weather forecasting, market price information—before introducing more complex systems. Build adoption gradually.

Infrastructure and Access

- **Expand Rural Electrification:** Prioritize solar-powered electricity infrastructure in farming communities. Without reliable power, digital tools remain out of reach. Community charging hubs could serve as an interim solution.
- **Affordable and Universal Internet Access:** Negotiate reduced data tariffs for agricultural communities and explore community-owned internet infrastructure. Offline-first AI applications should be prioritized.
- **Low-Cost Device Programs:** Develop subsidy or loan schemes through agricultural cooperatives to enable farmers to acquire basic smartphones at affordable rates.

Policy and Institutional Support

- **State-Level Strategy for Digital Agriculture:** Develop and implement a coordinated strategy for AI in agriculture in Adamawa State that explicitly addresses the needs and constraints of smallholder farmers, aligned with national digital agriculture frameworks.
- **Public-Private Partnerships:** Foster collaboration between the Adamawa State government, telecommunications companies, tech developers, and agricultural organizations to create affordable, context-appropriate solutions.
- **Continuous Monitoring and Evaluation:** Establish mechanisms to track adoption rates, usage patterns, and impact over time, allowing policies and tools to evolve in response to real-world experience in the state.

References

Adamawa State Government. (2026). A brief history of Adamawa State. Retrieved from https://adamawastate.gov.ng/history/

Ahmadu, A. S., Takwate, K. T., & Malgwi, Y. M. (2024). Analysis of emerging trends in artificial intelligence for education and agricultural extension in Nigeria. *Discover Artificial Intelligence*, 4(2), 110–120. https://doi.org/10.1007/s44163-024-00163-y

Ajith, S., & Vijayakumar, S. (2025). Yield prediction, pest and disease diagnosis, soil fertility mapping, precision irrigation scheduling, and food quality assessment using machine learning and deep learning algorithms. *Discover Food*, 5, 1–22. https://doi.org/10.1007/s44187-025-00338-1

Alliance for a Green Revolution in Africa [AGRA]. (2026). Nigeria's digital agriculture push: Transforming extension services for millions of smallholder farmers. *Africa Sustainability Matters*. Retrieved from https://africasustainabilitymatters.com/nigerias-digital-agriculture-push-aims-to-transform-extension-services-for-millions-of-smallholder-farmers/

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Creswell, J. W. (2014). Research design: Qualitative, quantitative, and mixed methods approaches (4th ed.). SAGE Publications.

Essien, A., Okafor, C., & Nwankwo, S. (2024). Exploring socio-cultural influences on generative AI engagement in Nigerian higher education and rural communities. *Smart Learning Environments*, 11, 63. https://doi.org/10.1186/s40561-024-00287-9

International Food Policy Research Institute [IFPRI]. (2023). Agricultural transformation in Nigeria: Trends, challenges, and opportunities. IFPRI Nigeria Strategy Report. Washington, DC: IFPRI.

Israel, G. D. (2023). Determining sample size. University of Florida IFAS Extension. Retrieved from https://edis.ifas.ufl.edu/pd006

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

Khan, A., Rehman, S., & Ahmed, F. (2024). Revolutionizing agriculture with artificial intelligence: Plant disease detection methods, applications, and their limitations. *Frontiers in Plant Science*, 15, 1356260. https://doi.org/10.3389/fpls.2024.1356260

National Bureau of Statistics [NBS]. (2024). Nigeria agricultural sector statistics 2023. Abuja, Nigeria: National Bureau of Statistics.

Nigerian Informer. (2026). States population in Nigeria (2026). Retrieved from https://nigerianinformer.com/states-population-in-nigeria/

Nunnally, J. C. (1978). Psychometric theory (2nd ed.). McGraw-Hill.

United Nations Development Programme [UNDP]. (2023). Nigeria human development report 2023: Agricultural transformation and inclusive growth. UNDP Nigeria. Abuja, Nigeria: UNDP.

van Dijk, J. A. (2024). The digital divide: A sociological analysis of access to new technologies (2nd ed.). SAGE Publications.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178. https://doi.org/10.2307/41410819

World Bank. (2025). Digital agriculture: Artificial intelligence and the future of food systems. Washington, DC: World Bank Group.

Zhang, N., Wang, M., & Wang, N. (2002). Precision agriculture—a worldwide overview. *Computers and Electronics in Agriculture*, 36(2–3), 113–132. https://doi.org/10.1016/S0168-1699(02)00096-0