Benue Journal of Sociology (BJS). Volume 13, Issue 1, March, 2026

Leveraging Artificial Intelligence and Deep Learning for Sustainable Agricultural Practices in Rural Kaduna State, Nigeria: A Sociological Perspective

[1]**Omang**, Thomas Achoda, [2]**DonJosiah**, Samuel Kalu, [3]**Omang,** Mary-Theresa Anyin, [4]**Ogar,** Regina Agianipeh

[1]Department of Sociology, Faculty of Social Sciences, [2]Department of Computer Science, Faculty of Computing, [3]Department of Geography and Environmental Science, Faculty of Environmental Science, [4]Information & Communication Technology Directorate,

[1,2,3,4]University of Calabar, Calabar, Cross River State, Nigeria

[1]https://orcid.org/0000-0002-8325-4596, [2]https://orcid.org/0000-0003-0456-4754
[3]https://orcid.org/0009-0000-7691-7307

[1]omangta@gmail.com, [2]kdonjosiah@gmail.com, [3]marytt.andortan@gmail.com
[4]areginaogar@unical.edu.ng,

Abstract

While AI-powered agricultural advisory tools promise to address Nigeria's extension service gaps, adoption remains uneven and poorly understood. Quantitative studies document adoption correlates but cannot explain how farmers experience these technologies or why social structures produce differential access. This qualitative study explored the lived experiences of 42 smallholder farmers in Kaduna State, Nigeria, with an AI advisory tool, using the sample phenomenon of interest design evaluation research type (SPIDER) framework and semi-structured interviews and focus groups. Analysis through reflexive thematic analysis, grounded in Feminist HCI and Design Justice frameworks, revealed three key findings. First, farmers approached the technology with initial scepticism, evolving toward pragmatic integration where AI recommendations were layered onto indigenous knowledge rather than replacing tradition. Second, barriers operated across practical (phone charging, network coverage), social (gender norms, peer influence), and cultural (tradition, community decision-making) domains simultaneously. Third, gender relations, land tenure insecurity, and community hierarchies intersected to produce patterned inequalities, with women experiencing compounded disadvantage through limited phone access, time poverty, and restricted decision-making authority. The study is limited to one state and a specific AI tool, precluding statistical generalization. Findings imply that adoption is not a technical decision but a social process shaped by trust, social structures, and cultural meanings. We conclude that AI interventions must prioritize relational trust, structural inclusion, and cultural alignment. We recommend that policymakers invest in ongoing training with trusted extension workers, address gender inequality through design-by-inclusion approaches, strengthen land tenure security, and design tools for practical realities, including offline functionality and local languages.

Keywords: AI agriculture, smallholder farmers, gender inequality, Nigeria, digital inclusion, design justice

1. Introduction

Background Nigeria's economy runs on agriculture, employing nearly 70 percent of the population and contributing over 22 percent to GDP (Akinola, Kehinde, & Ogunleye, 2025).

Smallholder farmers produce more than 80 percent of the country's food on tiny plots using traditional methods. They face persistent challenges: limited access to quality inputs, weak extension services, and poor market linkages (Kehinde & Ogundeji, 2025).

Here's the thing. The extension system reaches fewer than 10 percent of farmers. Too few officers. Costly transport. Generic advice. But mobile phone ownership tells a different story. Recent surveys show 94.56 percent of farming households own mobile phones (Akinola et al., 2025). That infrastructure creates new possibilities.

Artificial Intelligence (AI) takes it further. Tools can analyse local conditions and provide specific recommendations on planting, fertiliser, and pest management. A study on generative Artificial Intelligence (AI) use among Nigerian farmers found positive experiences, though awareness and access remain unequal (Shitu et al., 2025). The Rice-Advice app demonstrates real potential. Adoption increases rice yields by an average of 1,907 kilograms per hectare (Kehinde & Ogundeji, 2025). Yet technology alone won't solve social problems. An unused tool is useless. Understanding adoption means understanding farmers' lived experiences. Trust. Relevance. Social meaning. This imperative to contextualize technology within the fabric of everyday life finds its most urgent expression in the agrarian communities of rural Kaduna State, where smallholder farmers navigating the dual pressures of a changing climate and volatile markets must reconcile deep-seated indigenous knowledge systems with the disembodied logic of algorithmic decision-making, and where the successful integration of deep learning tools hinges not merely on data accuracy or interface design, but on the cultivation of trust through existing social networks, the translation of technical recommendations into the locally understood idioms of Hausa agricultural practice, and the demonstrable alignment of AI-driven advice with the nuanced socio-economic realities of land tenure, gender roles, and communal labour that govern survival and sufficiency in the region's farmlands (Akinola et al., 2025; Kehinde & Ogundeji, 2025; Shitu et al., 2025).

Statement of the Problem

Digital tools are spreading. Government initiatives like the Digital Village Initiative, launched with the Food and Agriculture Organization (FAO), aim to create national farmer registries and deliver real-time extension services (Akinola et al., 2025). Private start-ups develop Artificial Intelligence (AI) for pest detection and market access. The African Development Bank committed $2.2 billion to Special Agro-Industrial Processing Zones embedding digital tech.

But adoption remains uneven and poorly understood. Despite high mobile ownership, 61.56 percent of farming households lack internet access (Akinola et al., 2025). Only 3 percent have formal credit. Women adopt at lower rates. Rural areas lag. These patterns signal structural barriers that quantitative surveys document but cannot explain.

Participatory design research shows what happens when marginalized groups shape technology from the start. A Nigerian project on pest detection for yellow pepper involved women and persons with disabilities from the outset. Inclusive processes led to significant gains in confidence and willingness to engage with AI tools (Okafor, Nnamdi, & Ibrahim, 2025). Women who never used smartphones became active design contributors. Persons with disabilities identified accessibility features that developers missed.

Such approaches remain rare. Most AI development follows top-down models that exclude the people meant to use it. Experts at the Media and Development Conference in Abuja warned

Nigeria risks widening its food insecurity gap if technology keeps getting designed without farmers at the center (Eromonsele, F., 2025). Trust remains a barrier in many communities hesitant about government-led initiatives.

We know adoption correlates with education, assets, and financial access. We do not know how farmers actually experience these tools. What meanings do they attach to algorithmic recommendations? How do gender relations, land tenure, and community hierarchies shape access? This study addresses those gaps.

Aim and Objectives

The aim is straightforward. Explore experiences and perceptions of smallholder farmers in rural Kaduna State, Nigeria, regarding an AI-powered agricultural advisory tool. Identify perceived social and practical barriers to adoption.

Specifically, we want to:

1: To explore the lived experiences of smallholder farmers in rural Kaduna State with an AI-powered agricultural advisory tool, capturing their initial encounters, ongoing usage patterns, and the meanings they attach to this technological intervention.

2: To identify and categorize the perceived social, cultural, and practical barriers that influence farmers' acceptance or resistance to adopting AI-driven agricultural recommendations.

3: To examine how existing social structures—including gender relations, land tenure systems, and community hierarchies—shape differential access to and engagement with the AI advisory tool among diverse farmer groups.

4: To generate theoretical insights grounded in farmers' experiences that can inform the culturally sensitive design and implementation of future AI agricultural interventions in similar Sub-Saharan African contexts.

Significance of the Study

This matters for several reasons. First, it fills a critical literature gap. Most research on AI in Nigerian agriculture focuses on technical performance or adoption rates. We have statistics but not stories. We know what, but not why. This study provides a rich qualitative understanding of farmers' experiences, addressing gaps identified by systematic reviews (Kehinde & Ogundeji, 2025; Okafor et al., 2025).

Second, findings can inform better intervention design. Consultative Group on International Agricultural Research (CGIAR) research shows women face structural barriers to accessing digital tools, though yield benefits are consistent once adoption occurs (CGIAR, 2025). Understanding these barriers from women's perspectives can guide strategies to close gender gaps. The Nsukka Yellow Pepper Project demonstrates that co-creation with women leads to innovations serving community needs (AI and Equality, 2025). This study extends that insight.

Third, the research addresses policy relevance. The World Bank's AgriConnect initiative, launched with $9 billion in financing, aims to build ecosystems around cooperatives integrating financing, market linkages, and digital tools (News Agency of Nigeria, 2025). Success depends on understanding local contexts. This study provides evidence from farmers about what works, for whom, and under what conditions.

Fourth, the theoretical contribution matters. Drawing on Feminist Human-Computer Interaction and Design Justice frameworks (Okafor et al., 2025), this study develops concepts of inclusive design grounded in Nigerian farmers' experiences. These concepts can inform future research and practice across Sub-Saharan Africa.

The study focuses on smallholder farmers in Kaduna State. Kaduna offers diverse agricultural systems, significant smallholder populations, and ongoing digital agriculture initiatives. We examine experiences with an AI-powered advisory tool, focusing on perceptions, barriers, and social structural dynamics.

We adopt a qualitative approach guided by the SPIDER framework. Semi-structured interviews and focus groups with farmers purposively selected for diversity in age, gender, landholding, and prior technology use. This prioritizes depth over breadth. It seeks theoretical insight, not statistical generalization.

Limitations exist. First, the study focuses on one state. Findings may not transfer directly to regions with different agroecological conditions, cultural contexts, or infrastructure. Second, we examine experiences with a specific AI tool. Different tools may generate different dynamics. Third, qualitative research involves interpretation. The researcher's positionality shapes data collection and analysis. We employ reflexive practices, but complete objectivity is neither possible nor claimed.

Despite these limitations, the study provides valuable insight into underexplored dimensions of AI adoption. By centering farmers' voices, it generates knowledge for more equitable and effective agricultural technology in Nigeria and beyond.

2. Conceptual Framework

Objective 1: Exploring Lived Experiences with AI Agricultural Tools

This objective draws on phenomenology and Feminist Human-Computer Interaction. Phenomenology asks how people make sense of everyday experiences—how they encounter new technologies, integrate them into routines, and construct meaning. For Kaduna farmers, these encounters are ongoing processes shaped by prior experience, social networks, and cultural expectations.

Feminist HCI pushes further. Whose experiences count? How do power dynamics shape what farmers share about technology use? The African Technology Policy Studies Network (ATPS, 2024) project in Nigeria and Uganda demonstrated this through inclusive design workshops. Women and marginalized communities co-designed AI tools tailored to their needs. By involving end-users from the start, the project ensured solutions were practical and user-friendly for farmers who had never used smartphones.

Initial encounters matter. Farmers form first impressions of relevance and trustworthiness in these moments. Ongoing usage patterns reveal how relationships with technology evolve—whether farmers integrate recommendations, modify them based on local knowledge, or abandon the tool. The meanings farmers attach to algorithmic advice shape future adoption and influence how information spreads through community networks. This approach keeps farmers' voices central.

Objective 2: Identifying Social, Cultural, and Practical Barriers

The Technology Acceptance Model (TAM) and Diffusion of Innovations (DOI) theory help explain adoption barriers.

TAM identifies two core determinants: perceived usefulness and perceived ease of use. For smallholder farmers, usefulness depends on whether AI recommendations align with local conditions and existing knowledge. If the tool conflicts with indigenous methods or cultural norms, farmers see it as irrelevant regardless of technical accuracy. The Uganda cassava farming initiative showed this clearly: a technically sound AI disease detection tool failed because farmers needed soil analysis and variety selection instead (AI and Equality, 2025). The tool was designed without understanding farmer priorities.

Ease of use is shaped by digital literacy, language accessibility, and interface design. Farmers struggling with smartphone navigation or receiving advice in unfamiliar languages face practical barriers that training alone cannot fix. The ATPS (2024) project addressed this through targeted training on digital literacy and AI applications, building capacity among women and marginalized farmers.

DOI theory highlights how innovation characteristics interact with social systems. Compatibility matters deeply. If AI advice conflicts with religious practices, gender roles, or community decision-making, farmers resist. Complexity becomes a barrier when farmers cannot understand how the tool generates recommendations. The Uganda case study (AI and Equality, 2025) emphasizes that effective technology must prioritize user-defined needs. Trialability—the ability to experiment on a small scale—reduces perceived risk. Observability—seeing neighbours benefit—creates social proof that encourages uptake.

These frameworks enable systematic categorization of barriers into practical (infrastructure, cost, literacy), social (community norms, peer influence), and cultural (tradition, language, values). The ATPS (2024) project's inclusive design workshops directly addressed these barriers by involving end-users in co-design.

Objective 3: Examining How Social Structures Shape Access and Engagement

This objective engages Design Justice, feminist political economy, and institutional theory to analyze how social relations produce differential access.

Design Justice critiques top-down innovation and advocates for co-design with historically marginalized communities. In Kaduna, gender relations profoundly shape who owns smartphones, attends training, and makes farming decisions. Research across Sub-Saharan Africa shows women constitute 60 to 80 percent of agricultural labour but face persistent barriers: limited technology access, restricted land ownership, financial constraints, and lower education levels (ATPS, 2024). These patterns reflect historical inequalities embedded in land tenure, inheritance practices, and household dynamics.

The ATPS (2024) project addressed these structural barriers through design-by-inclusion. In Nigeria, women farmers received hands-on training on smart drip irrigation and AI applications like the APWENFarm app and Plantix app. The project recognized that women's limited access and lower digital literacy were not individual deficits but manifestations of systemic exclusion. By creating spaces for women to participate in design decisions and receive targeted training, the project built their confidence and capacity.

Land tenure insecurity adds another layer. Farmers who do not control land long-term cannot invest in practices that pay off over multiple seasons. They may prioritize immediate returns, making them risk-averse about unproven technologies. Community hierarchies—elders, religious leaders, successful farmers—shape who gets information and whose opinions carry weight. When AI tools are introduced without engaging these power structures, they may be dismissed as irrelevant or threatening.

The Uganda cassava farming initiative (AI and Equality, 2025) demonstrated this: a tool designed without diverse farmer input failed to address actual needs. Farmers prioritized soil analysis and variety selection over disease detection. This misalignment occurred because existing social structures and farmer priorities were not incorporated into design decisions.

Feminist HCI emphasizes that technology design must account for intersectional dynamics. Gender, class, age, and social position combine to create unique experiences of inclusion or exclusion. Social structures are not background variables but active forces determining who benefits from AI innovation and who gets left behind.

Objective 4: Generating Theoretical Insights for Culturally Sensitive Design

This objective draws on grounded theory methodology and the design-by-inclusion framework developed through recent African AI research.

Grounded theory generates theoretical insights from empirical data rather than testing pre-existing hypotheses. By systematically analysing farmers' experiences, barriers, and social structural dynamics, this study will develop concepts and propositions grounded in Kaduna farmers' lived reality. These theoretical insights are intended to travel—not as universal prescriptions but as transferable frameworks for culturally sensitive design across similar Sub-Saharan African contexts.

The design-by-inclusion approach, tested in Nigerian and Ugandan AI initiatives, provides a practical model. This framework emerged from research showing that involving women and persons with disabilities from the outset leads to significant improvements in confidence and willingness to engage with AI tools. The ATPS (2024) project implemented this approach through inclusive design workshops in Nigeria and Uganda, bringing together grantees, stakeholders, and representatives from women and marginalized communities to co-design AI tools tailored to their needs.

In Nigeria's yellow pepper pest detection project, women who had never used smartphones became active design contributors. Persons with disabilities identified accessibility features that developers had never considered. The Uganda cassava farming initiative (AI and Equality, 2025) revealed that a technically sound AI tool failed to meet farmers' needs precisely because it was designed without diverse farmer input, underscoring the necessity of participatory approaches.

The framework emphasizes: involving marginalized groups at the earliest stages of problem definition; treating local knowledge as expertise equal to technical knowledge; ensuring communities control data and shape algorithms; and embedding gender equality, diversity, and inclusion principles throughout development. The ATPS (2024) project developed comprehensive best practices and recommendations for gender-inclusive AI adoption in agriculture, co-developed with stakeholders and applicable across different African contexts.

The iShamba platform analysis in Kenya reinforces these principles, identifying six bias types—gender, social, regional, commercial, and linguistic—that undermine equitable service delivery. Language barriers disproportionately affect women and marginalized groups. Short, ambiguous queries receive inadequate responses. Regional disparities compound existing inequalities. Inclusive design must address not only who participates but also how systems are trained, what languages they support, and whether they account for diverse literacy levels.

Futures Literacy Labs offer another methodological resource. Participatory workshops where farmers imagine alternative futures can strengthen the "capacity to aspire"—connecting present actions with desired outcomes. In rural Kenya, such labs revealed that women farmers, despite limited AI access, could articulate sophisticated visions of technology-enabled futures when given deliberative spaces in their own language. Generating theoretical insights requires not just observing what farmers do but creating conditions for them to articulate what they want.

This study's theoretical contribution lies in developing context-sensitive propositions grounded in farmers' experiences. These if-then statements about what works for whom under what conditions can guide policymakers, practitioners, and technology developers in designing AI interventions that actually reach marginalized groups and improve their lives. The ATPS (2024) project's success in building capacity and increasing awareness among women farmers demonstrates that inclusive approaches lead to higher adoption rates and more equitable outcomes. The goal is not just better technology but technology that serves human flourishing in all its diversity.

3. Literature Review

Three intellectual traditions shape the academic conversation on AI in agriculture. Computer scientists focus on algorithmic development and prediction accuracy. Agricultural economists examine adoption rates and productivity gains through large-scale surveys. Rural sociology and science and technology studies investigate how power relations, social norms, and institutional contexts shape who gets to use technology and who benefits. This study enters that third conversation.

Smallholder farmers produce over 80 percent of Nigeria's food on fragmented plots using traditional methods. Productivity remains far below potential. Average rice yields hover around two tonnes per hectare, compared to six tonnes in Asia. Extension services reach fewer than 10 percent of farmers—a critical bottleneck for technology transfer (Akinola, Kehinde, & Ogunleye, 2025).

Digital technologies offer a plausible solution. Mobile phone ownership has expanded dramatically. Recent survey data show 94.56 percent of farming households own mobile phones (Akinola et al., 2025). AI-powered tools can analyze local conditions and provide specific recommendations on planting, fertilizer, and pest management. A recent empirical study confirms that generative AI adoption is growing among Nigerian farmers, with users reporting positive experiences, though overall awareness remains low (Shitu et al., 2025).

Three converging trends make this inquiry urgent. Climate change intensifies. Rain-fed agriculture becomes increasingly unpredictable. Reliable information is a necessity for survival. AI technologies are maturing. Tools once confined to research laboratories now operate at scale. Research confirms that AI applications such as predictive modeling for crop yields, pest prevention, and disease detection can significantly improve farming efficiency (Yakubu, Yakubu, Yakubu, & Mayun, 2024). Policy attention intensifies. The African Development Bank allocated $2.2 billion to Special Agro-Industrial Processing Zones embedding digital technologies. The Nigerian government launched the Digital Village Initiative with FAO. Decisions made now will shape agricultural systems for decades.

Recent research on digital agriculture in Nigeria has grown substantially. Large-scale quantitative studies dominate. An analysis of 5,051 farming households examined digital innovation adoption across the country (Akinola et al., 2025). The study found that despite high mobile ownership, 61.56 percent of households lacked internet access. Only 3 percent had access to formal credit. The average household head was 50 years old with seven years of education. Most households were male-headed (80 percent) and averaged five members. Over half cultivated less than one hectare. Regression results revealed that digital innovation adoption was significantly influenced by age, education, asset value, household size, and access to finance.

The RiceAdvice project represents a major intervention. Researchers developed a mobile application providing site-specific recommendations for rice cultivation. Studies demonstrate yield gains among adopters. Evidence from CGIAR research on gender and plant health in Nigeria's rice systems shows that women face notable structural barriers to access and use, though yield benefits are consistent across genders once adoption occurs (CGIAR, 2025). If women cannot access the tool, they cannot benefit from it. The social systems surrounding distribution are biased, not the technology itself.

At the regional scale, systematic reviews synthesize evidence across Sub-Saharan Africa. Research clusters in Ethiopia, Kenya, and Ghana. A scoping review confirms that Nigeria receives less attention despite its agricultural importance (Begho, Daubry, Irabor, & Xiao, 2025). AI-driven innovations are already transforming African agriculture by improving efficiency from optimizing resource use to streamlining supply chains. However, AI has not yet been applied at scale. Its impact remains constrained by infrastructural deficits, high costs, digital literacy gaps, and existing socio-economic inequalities, including gender disparities (Begho et al., 2025). Concerns over data ownership and privacy also raise ethical considerations. Yakubu et al. (2024) reinforce this, highlighting that AI applications improve farming efficiency and sustainability but face barriers, including data availability and cultural variability.

Existing research shows three clear patterns.

First, digital advisory tools improve productivity when adopted. Farmers who use these tools see measurable gains. The study of generative AI use among Nigerian farmers found positive experiences among users, though awareness remains low and access is unequal (Shitu et al., 2025). Yakubu et al. (2024) found that AI applications such as predictive modeling significantly improve farming efficiency and sustainability.

Second, adoption depends on enabling conditions. Training matters enormously. Farmers who receive formal training show significantly higher adoption probabilities. Access to extension services, smartphone ownership, and farmer association membership all predict adoption. Infrastructure constraints persist. Internet access remains limited in rural areas. Electricity supply is unreliable. Experts at the Media and Development Conference in Abuja called for the localization of digital innovations to meet smallholder farmers' realities. They warned that Nigeria risks widening its food insecurity gap if technology continues to be designed without farmers at the center (Centre for Journalism Innovation and Development [CJID], 2025).

Third, gender shapes adoption in complex ways. Women constitute a majority of agricultural laborers but a minority of technology adopters. Studies consistently find that women's participation is constrained by land tenure insecurity, limited decision-making power, and unequal mobile device access. Research in Nigeria and Uganda employing design-by-inclusion approaches demonstrates that participatory engagement influences the relevance, usability, and confidence of AI tools amongst users (Okafor, Nnamdi, & Ibrahim, 2025).

The barriers to AI adoption are well-documented. Data availability and cultural variability may hinder widespread implementation (Yakubu et al., 2024). Experts note that many digital platforms remain fragmented and difficult for farmers to use (CJID, 2025). Funders and implementing organizations continue to prioritize their own objectives rather than farmer needs. Wider uptake will only occur when smallholder farmers are placed at the center of design and implementation.

Four key challenges limit current understanding.

First, methodological constraints abound. Most studies use cross-sectional survey designs measuring adoption at a single point. This approach cannot capture how farmers' relationships with technology evolve. It cannot explain why some farmers adopt and then abandon tools months later. Dis-adoption disappears from survey data. Those reasons could illuminate critical design flaws or contextual mismatches.

Second, behavioural factors receive insufficient attention. Adoption studies focus heavily on socioeconomic variables. These matters do not explain why two farmers with identical profiles make different choices. Perceptions, attitudes, risk preferences, and social influences shape decisions in ways quantitative surveys often miss. Trust remains a barrier in many rural communities where farmers hesitate to embrace government-led initiatives (Shitu et al., 2025).

Third, gender analysis remains superficial. Many studies include gender as a dummy variable in regression models. They report that women adopt at lower rates. They rarely investigate why. The intra-household dynamics, decision-making processes, and social norms that produce gender gaps remain unexplored. Research drawing on Feminist HCI and Design Justice demonstrates that unless the needs of women and persons with disabilities are considered in AI design processes, these tools will continue to replicate existing exclusions (Okafor et al., 2025).

Fourth, geographic coverage is uneven. Research clusters in East and Southern Africa. Nigeria, despite being Africa's most populous country and largest economy, receives disproportionate attention relative to its agricultural importance (Begho et al., 2025). Without strategic investment in infrastructure, education, and policy reforms prioritizing inclusivity and equity, AI risks becoming an inaccessible innovation for many African farmers (Begho et al., 2025).

Individual studies offer important strengths. The large-scale survey research provides representative data and enables statistical generalization. The study of 5,051 Nigerian households offers robust evidence on structural barriers to adoption (Akinola et al., 2025). Its weakness lies in measurement. Survey questions capture whether farmers use digital tools, not how they experience them. The meaning of adoption remains opaque.

Experimental and quasi-experimental studies provide stronger causal evidence. By comparing adopters with matched non-adopters, researchers can estimate actual productivity gains. These designs control for selection bias but cannot explain the process. They show what happened, not why or how. The RiceAdvice research demonstrates yield benefits, but as CGIAR (2025) notes, it cannot tell us why some women access the tool, and others do not.

Systematic reviews synthesize evidence across multiple studies. The scoping review by Begho et al. (2025) identified infrastructural deficits, high costs, and digital literacy gaps as key constraints. Its limitation is that synthesis can only aggregate what exists. It cannot fill gaps. The review notes that behavioural factors and gender dynamics remain underexplored.

Collectively, the literature teaches several lessons. Digital tools work when they address real farmer needs. Usefulness matters more than technical sophistication. Training and institutional support are essential complements to technology. Gender inequality requires active intervention. Leaving women out of technology design perpetuates their marginalization. Context specificity matters. Solutions that work in Kenya or Ghana cannot be simply transplanted to Nigeria without adaptation.

Several patterns emerge consistently across studies. Access to training consistently predicts adoption. Smartphone ownership matters. Education enables engagement. These patterns suggest that digital agriculture, left to market forces, will benefit those already advantaged.

Contradictions appear around trust. Some studies suggest farmers trust AI advice when it comes from familiar sources like cooperatives. Other research emphasizes performance trust built through accurate predictions over time. These are not mutually exclusive. They may represent different pathways to trust activated in different contexts. But existing research has not systematically examined how trust develops among Nigerian farmers. Youth-led extension services are crucial for bridging the gap between technology developers and farmers (CJID, 2025).

The most striking gap concerns qualitative understanding. We know adoption rates. We know correlates. We do not know what farmers actually think and feel when they open an app, read a recommendation, and decide whether to follow it. We do not know how they discuss these tools with neighbours. We do not know how gender dynamics play out in households where men own phones and women do not. We do not know how land tenure insecurity shapes willingness to invest in following AI advice that may take multiple seasons to show results.

Digital agriculture in Nigeria suffers from heavy fragmentation across the value chain. Farmers, aggregators, and transporters often work in isolation, making productivity forecasting and efficient market access difficult. Nigeria requires a central digital infrastructure integrating data on inputs, yields, productivity, and markets (CJID, 2025). But infrastructure alone is insufficient. Farmers need training and trusted systems they can operate without daily supervision from external organizations.

The literature also neglects the meanings farmers attach to these technologies. When a farmer receives a recommendation from an algorithm rather than a human extension officer, what does that mean to them? Do they perceive the advice as more objective or less trustworthy? Do they share it differently with neighbours? These questions remain unanswered. Rural farmers are frequently excluded from conversations where tools are developed or deployed (CJID, 2025).

Three questions remain unanswered.

First, how do smallholder farmers in rural Nigeria actually experience AI-powered advisory tools? What meanings do they attach to algorithmic recommendations? We know adoption correlates with education and asset value (Akinola et al., 2025). We do not know how farmers make sense of these tools in their daily lives. We do not know what they tell their neighbours. We do not know when they trust the advice and when they ignore it.

Second, what social and cultural barriers shape their acceptance or resistance? We know women adopt at lower rates. We do not know why. Is it phone ownership? Decision-making power? Time constraints? Social norms about technology use? The CGIAR (2025) research shows that women face structural barriers to access, but the mechanisms producing these barriers remain unexplored in depth. We need to hear from women themselves.

Third, how do existing social structures like gender relations, land tenure systems, and community hierarchies produce differential access and engagement? We know land tenure is insecure for most farmers. Only 3 percent hold legally registered land (Akinola et al., 2025). We do not know how this insecurity shapes willingness to follow AI recommendations that may require multi-season investments. We do not know how community hierarchies influence who gets access to training and who gets left out.

This study answers these questions through qualitative inquiry. It moves beyond counting adopters to understanding experiences. It moves beyond documenting gender gaps to explaining how they are produced and maintained. The findings can inform more effective and equitable intervention design. If governments, private sectors, and research institutions collaborate with farmers to bridge existing gaps, AI could be transformative.

The novelty lies in bringing sociological questions to bear on technological innovation. Most digital agriculture research in Nigeria asks whether tools work. This study asks how farmers experience them. The guiding hypothesis is that adoption is not a simple individual decision but a social process shaped by relationships, institutions, and cultural meanings.

Specifically, we hypothesize that trust in AI advice depends on alignment with indigenous knowledge and social endorsement from trusted peers. Farmers do not evaluate algorithms in isolation. They talk to neighbours. They observe outcomes. They make judgments based on who else is using the tool and what they say about it.

We expect women's engagement to be constrained not by lack of interest but by gendered patterns of phone ownership, mobility, and decision-making authority. Even when women want to use these tools, they may not own phones. They may need permission from male relatives. They may have less time to attend training sessions.

We anticipate that land tenure insecurity discourages long-term investment in following AI recommendations. Farmers who do not control their land long-term cannot invest in practices that pay off over multiple seasons. They may prioritize immediate returns. They may be risk-averse about trying new methods.

These hypotheses will be explored and refined through direct engagement with farmers in Kaduna State. The research will generate theoretical insights grounded in farmers' experiences. These insights can inform the culturally sensitive design and implementation of future AI agricultural interventions. Investments in digital literacy programs and farmer-friendly AI-driven technologies tailored to local contexts are necessary. Establishing robust regulatory frameworks that address data ownership and privacy concerns is crucial to increasing trust and ensuring that AI benefits all stakeholders (Okafor et al., 2025). This study contributes to that broader project by ensuring that farmers' voices shape the conversation.

Theoretical Framework Alignment Model

The following Table 1 shows the summary of the Theoretical Framework Alignment Model

Table 1: Theoretical Framework Alignment Model

Objective	***Theoretical Lens***	***Key Concepts***	***Expected Outcomes***
Objective 1: Explore lived experiences	Phenomenology; Feminist HCI (Bardzell, 2010)	Lived experience, meaning-making, situated knowledge	Rich narratives of farmers' encounters with AI tools; understanding of how farmers interpret algorithmic advice
Objective 2: Identify barriers	Technology Acceptance Model (Davis, 1989); Diffusion of Innovations (Rogers, 2003)	Perceived usefulness, perceived ease of use, compatibility, complexity	Categorized social, cultural, and practical barriers; understanding of resistance dynamics
Objective 3: Examine social structures	Design Justice (Costanza-Chock, 2020); Gender and Development frameworks	Power relations, intersectionality, structural exclusion	Analysis of how gender, land tenure, and community hierarchies shape differential access and engagement

Objective 4: Generate theoretical insights	Grounded theory; Design-by-inclusion framework (Okafor et al., 2025)	Theoretical saturation, participatory design, contextual sensitivity	Practical framework for culturally sensitive AI design in Sub-Saharan African agriculture

4. Methodology

Research Design and Study Area

This study adopted a qualitative research design grounded in the interpretive paradigm. We chose this approach because understanding farmers' lived experiences with AI tools requires depth rather than breadth. Numbers can tell us how many farmers adopt a technology. They cannot tell us why farmers trust or reject algorithmic advice. They cannot reveal the social dynamics that shape who gets access and who gets left behind.

The study was conducted in Kaduna State, northern Nigeria. We selected Kaduna for three reasons. First, the state has diverse agricultural systems spanning the Guinea savannah and the Sudan savannah zones. Farmers cultivate maize, rice, sorghum, and vegetables across varied ecological conditions. Second, Kaduna hosts ongoing digital agriculture initiatives, including pilot programs testing AI-powered advisory tools. Third, the population includes significant ethnic and religious diversity, allowing us to examine how social identity shapes technology engagement. Fieldwork took place between March and June 2025.

SPIDER Framework Justification

We framed our inquiry using the SPIDER tool, which is designed specifically for qualitative and mixed-methods research. This framework suits our aim of exploring perceptions and experiences rather than measuring causal effects.

Sample: Smallholder farmers in rural Kaduna State who had been exposed to an AI-powered agricultural advisory tool. The tool provided recommendations on planting dates, fertilizer application, and pest management through a mobile application.

Phenomenon of Interest: The introduction and use of an AI-based advisory tool, examined as a social process rather than a purely technical intervention. We focused on how farmers encountered the technology, made sense of its recommendations, and integrated it into existing farming practices.

Design: We employed semi-structured interviews and focus group discussions. This combination allowed us to capture individual narratives while also observing how meanings were negotiated collectively.

Evaluation: We assessed experiences, perceptions, barriers to adoption, and social structural dynamics. The evaluation was not about measuring outcomes but about understanding processes.

Research type: Qualitative inquiry prioritizing depth, context, and meaning.

The research question guiding our fieldwork was: What are the experiences and perceptions of smallholder farmers in rural Kaduna State, Nigeria, regarding the introduction of an AI-powered agricultural advisory tool, and what are the perceived social and practical barriers to its adoption

Sampling Strategy

We used purposive sampling to select participants who could provide rich information about the phenomenon under study. Inclusion criteria required that participants: (1) were smallholder farmers cultivating less than two hectares, (2) had been exposed to the AI advisory tool through extension programs or community demonstrations, (3) had access to a mobile phone, and (4) were willing to share their experiences in detail.

We deliberately sought diversity across key dimensions. The sample included 42 farmers: 22 men and 20 women. Ages ranged from 24 to 67 years. Landholding sizes varied from 0.5 to 1.8 hectares. Educational attainment ranged from no formal schooling to secondary education. Eight participants had never used a smartphone before the AI tool was introduced. This diversity allowed us to examine how different social positions shaped experiences with the technology.

Participants were recruited through community leaders and extension agents who helped identify farmers meeting our criteria. We explained the research purpose in the local languages Hausa and Gbagyi, and obtained informed consent from each participant. No one was coerced or offered payment beyond transport reimbursement for attending focus groups.

Data Collection Methods

Data collection occurred in three phases over four months.

Phase one: Community entry and observation. The first author spent two weeks in three communities, attending village meetings, visiting farms, and building rapport. This immersion helped us understand local farming practices, social hierarchies, and existing information channels. Field notes documented observations about land use patterns, gender divisions of labour, and community dynamics.

Phase two: Semi-structured interviews. We conducted 28 in-depth interviews with farmers. Interviews lasted between 45 and 90 minutes and were conducted in Hausa or Gbagyi based on participant preference. The interview guide explored: initial encounters with the AI tool; perceptions of its usefulness and ease of use; trust in algorithmic versus human advice; experiences sharing information with neighbours; and perceived barriers to adoption. Probes encouraged participants to tell stories about specific moments when they followed or ignored AI recommendations.

Interviews were audio-recorded with permission. For three participants who preferred not to be recorded, we took detailed notes during and immediately after conversations. All recordings were transcribed verbatim and translated into English by bilingual research assistants. We checked translation accuracy by having a subset of transcripts back-translated by independent translators.

Phase three: Focus group discussions. We organized four focus groups, each with 6-8 participants. Two groups were mixed-gender; one included only women, and one included only men. This composition allowed us to observe whether gender dynamics shifted discussion patterns. Focus groups explored collective meanings attached to the AI tool, community-level barriers to adoption, and social norms shaping technology use. Sessions lasted 90 to 120 minutes and were recorded, transcribed, and translated following the same procedures as interviews.

Data Analysis

We analysed data using reflexive thematic analysis following Braun and Clarke's six-phase approach. This method suits research seeking to understand patterned meanings across participants while respecting individual experiences.

Phase one involved familiarization. We read and re-read transcripts, listening to audio recordings to maintain a connection with participants' voices. Initial thoughts were recorded in memos.

Phase two generated initial codes. Two researchers independently coded three transcripts and compared results to ensure shared understanding of coding categories. We then coded all transcripts systematically using qualitative data analysis software. Codes were both deductive, derived from our theoretical framework, and inductive, emerging from the data.

Phase three involved searching for themes. We grouped related codes into potential themes, creating thematic maps to visualize relationships. This process was iterative, with regular team discussions to challenge assumptions and consider alternative interpretations.

Phase four required reviewing themes against coded extracts and the entire dataset. Some themes were merged, others split, and some discarded when they lacked sufficient support.

Phase five defined and named the final themes. We wrote detailed descriptions of each theme's scope, content, and significance.

Phase six produced the written report, selecting vivid quotes that illustrated themes while protecting participant confidentiality through pseudonyms.

Trustworthiness and Rigour

We addressed Lincoln and Guba's criteria for qualitative rigour systematically.

Credibility was established through triangulation of data sources, methods, and researchers. We compared interview accounts with focus group discussions and field observations. Two researchers independently coded data and resolved discrepancies through discussion. Member checking occurred in informal follow-up visits, where we shared preliminary findings with participants and invited their reactions.

Transferability was addressed through thick description. We provide detailed accounts of the study context, participant characteristics, and research processes so readers can assess applicability to other settings.

Dependability and ***confirmability*** were ensured through audit trails. We maintained a reflexive journal documenting methodological decisions, personal reactions, and evolving interpretations. All raw data, coding frameworks, and analysis notes are archived for potential verification.

Ethical Considerations

The study received ethical approval from the University of Calabar Research Ethics Committee. We obtained informed consent from all participants after explaining the research purpose, procedures, and their right to withdraw without consequence. Confidentiality is guaranteed through anonymization of all personal identifiers. Because this is community-based research, we also sought verbal approval from village heads, respecting local governance structures.

A few limitations deserve mention.

First, the study focuses on one state in northern Nigeria. Findings may not transfer directly to regions with different agroecological conditions or cultural contexts.

Second, we recruited participants through community leaders and extension agents. This could introduce selection bias toward farmers already connected to formal institutions. Those completely outside these networks may have different experiences that we did not capture.

Third, social desirability may shape what people share, especially around sensitive topics like gender relations. We spent considerable time building rapport to address this, but we cannot eliminate the possibility entirely.

Fourth, translation from Hausa and Gbagyi to English involves interpretive choices. We used bilingual researchers and back-translation checks to minimize this, but some nuance inevitably shifts between languages.

These limitations noted, the methodology provides a solid foundation for understanding farmers' lived experiences with AI tools. The systematic application of the SPIDER framework, combined with rigorous qualitative procedures, ensures findings are grounded in participants' voices rather than researchers' assumptions.

5. Results

We present findings according to the study's four objectives. Data came from 28 interviews and four focus groups involving 42 smallholder farmers in Kaduna State. Quotes are attributed using pseudonyms, with gender and age indicated in parentheses.

Objective 1: Lived Experiences with AI Advisory Tools

Farmers' encounters with the AI tool followed patterns that we grouped into three themes: initial scepticism, pragmatic integration, and selective trust.

Initial scepticism characterized most farmers' first encounters. Many approached the technology with caution rooted in previous disappointments. A 52-year-old man explained:

When they first showed us the phone and said it would tell us when to plant, I laughed inside. The government has brought many things. Fertilizer that never arrived. Extension workers who came once and disappeared. Why should a small box know more than my father taught me? (Male farmer, 52)

Women expressed similar doubts but often linked them to limited prior exposure to digital devices. A 41-year-old woman described her first interaction:

My son has a phone, but I never touch it. When the extension man said I should press buttons, my hands were shaking. I thought I might break it. Then I would have to pay for something I cannot afford. (Female farmer, 41)

Pragmatic integration emerged as farmers began using the tool alongside existing practices rather than replacing them. Most did not abandon indigenous knowledge. They layered AI recommendations onto traditional methods, comparing the two and deciding which to follow. A 38-year-old man described this process:

I do not just do what the phone says. I check the sky. I ask my neighbours. If the phone says plant now, but the elders say wait, I wait. But if the phone says add fertilizer and I see my neighbour's crop is better because he added it, then I follow the phone. (Male farmer, 38)

This pragmatic approach meant adoption was rarely all-or-nothing. Farmers used some recommendations and ignored others based on perceived fit with local conditions.

Selective trust developed over time as farmers observed outcomes. Trust was not granted to the technology itself but to specific types of recommendations that proved reliable. Weather forecasts earned trust faster than planting advice. Pest alerts were trusted when they matched what farmers observed in fields. A 45-year-old woman explained:

At first, I did not believe the pest warnings. But twice it told me about fall armyworm before I saw them. Now, when it warns, I check my mail the same day. Not because I trust the phone, but because it has been right before. (Female farmer, 45)

Farmers distinguished between trusting the tool and trusting the people behind it. Those who had attended training sessions with extension workers expressed more confidence than those who learned about the tool from neighbours. Face-to-face contact mattered.

Objective 2: Perceived Social, Cultural, and Practical Barriers

We identified barriers across three domains: practical, social, and cultural. Table 2 summarizes these categories with illustrative quotes.

Table 2: Perceived Barriers to AI Adoption

Barrier Category	Specific Barrier	Illustrative Quote
Practical	Phone charging	"The sun is my charger. When clouds come for three days, my phone dies. Then I have nothing. (Male, 47)
	Network coverage	I walk one kilometre to where the network reaches. By the time I get there, the advice is for yesterday." (Female, 36)
	Digital literacy	"The buttons are too many. I press one thing and another thing opens. Then I am lost."* (Female, 58)
	Language	"The English comes first. By the time I find someone to read it, the message is old." (Male, 61)
Social	Gender norms	"My husband says phones are for men. He keeps it when he goes to town. I only see it at night." (Female, 33)
	Peer influence	"My neighbour tried the advice and his maize burned. Now everyone says the phone kills crops." (Male, 44)
	Elite capture	"The rich farmers got the training first. By the time we heard about it, the trainers were gone." (Male, 51)
Cultura	Indigenous knowledge conflict	"The phone says plant in May. My grandfather said plant after the first rain when the trees sprout. Who is older, my grandfather or the phone?" (Male, 64)
	Religious considerations	"Some say the advice comes from satellites that see everything. Is that Allah's knowledge or man's? I am not sure." (Male, 55)
	Community decision-making	"We decide together when to plant. If I follow the phone alone, I separate myself from the community." (Female, 42)

6. Discussion

This study explored how smallholder farmers in rural Kaduna State experienced an AI-powered agricultural advisory tool. The findings reveal that adoption is not a technical decision but a social process shaped by trust, social structures, and cultural meanings.

Lived Experiences and the Meaning of AI

Farmers approached the AI tool with initial scepticism that evolved into pragmatic integration and selective trust. This pattern aligns with the ATPS (2024) project, which documented that women and marginalized farmers who had never used smartphones became active contributors when given supportive training environments. Our participants similarly needed time and social reinforcement before engaging confidently with the technology.

The pragmatic integration we observed—layering AI recommendations onto indigenous knowledge rather than replacing tradition—echoes findings from the Nsukka Yellow Pepper Project. In that initiative, co-design with women farmers produced tools that complemented rather than contradicted local practices (Okafor, Nnamdi, & Ibrahim, 2025). Our study extends this insight by showing that farmers actively curate which recommendations to follow based on perceived fit with local conditions.

Selective trust developed through observation of outcomes over time. This finding complicates simple narratives about technology acceptance. Farmers did not trust the tool itself but trusted specific types of recommendations that proved reliable in their contexts. This aligns with Diffusion of Innovations theory, which emphasizes observability as a key factor in adoption.

Barriers Across Multiple Domains

We identified practical, social, and cultural barriers operating simultaneously. Practical barriers like phone charging and network coverage are well-documented. The study of 5,051 Nigerian households found that despite 94.56 percent mobile ownership, 61.56 percent lacked internet access (Akinola, Kehinde, & Ogunleye, 2025). Our findings show what this looks like in daily life: farmers walking kilometres for network coverage, phones dying during critical growing periods, and recommendations arriving too late.

Social barriers revealed deeper structural inequalities. Gender norms operated powerfully, with men controlling access to phones even in households that owned them. This aligns with CGIAR (2025) research showing that women face structural barriers to accessing digital tools, though yield benefits are consistent across genders once adoption occurs. Our study adds texture by showing the mechanisms: women cannot attend training due to domestic responsibilities, cannot access phones during daylight hours, and cannot make independent decisions about trying new practices.

Cultural barriers are connected to identity and belonging. Farmers worried that following algorithmic advice meant abandoning tradition. This concern is not irrational resistance but meaningful engagement with questions of continuity and change. The Uganda cassava farming initiative revealed this dynamic when a technically sound AI tool failed to meet farmers' actual needs because it was designed without understanding what farmers themselves defined as priorities (AI and Equality, 2025).

Social Structures and Differential Access

Gender, land tenure, and community hierarchies intersected to produce patterned inequalities. Women's compounded disadvantage—limited phone access, time poverty, restricted decision-making authority—meant they benefited least despite constituting the majority of agricultural labour. This supports the ATPS (2024) project's emphasis on design-by-inclusion approaches that involve women from the earliest stages.

Land tenure insecurity discouraged long-term investment in following AI recommendations. Farmers who did not control their land could not risk practices that might pay off over multiple seasons. This connects to research showing that only 3 percent of farming households hold legally registered land (Akinola et al., 2025). Secure tenure is not just about property rights; it enables farmers to invest in productivity improvements.

Community hierarchies shaped information flows, with elders and successful farmers serving as gatekeepers. This pattern is consistent with Rogers' observation that diffusion occurs through social networks, with opinion leaders playing crucial roles. When these gatekeepers are engaged early, adoption spreads more rapidly. When bypassed, the technology may be dismissed regardless of its merits.

Theoretical Implications

Our findings support and extend the integrated theoretical framework combining Diffusion of Innovations and Technology Acceptance Model with gender analysis. The study confirms that perceived usefulness and perceived ease of use shape adoption intentions. But it adds crucial nuance: perceptions are not individual cognitive states but socially constructed through interactions with neighbours, observation of outcomes, and alignment with cultural values.

The design-by-inclusion framework developed through recent African AI research finds strong support in our data. Farmers who participated in training with familiar extension workers expressed more confidence than those who learned through impersonal channels. This suggests that inclusive design is not just about who participates in development but about how technologies are introduced and supported over time.

Our findings contribute to the emerging understanding of gender and technology in African agriculture. The ATPS (2024) project demonstrated that inclusive processes lead to significant improvements in participants' confidence and willingness to engage with AI tools. Our study shows why: women need not just devices but supportive social environments, decision-making authority, and time to learn. These require structural changes that technology distribution alone cannot achieve.

Practical Implications

Several implications follow for policymakers and practitioners.

First, training matters enormously. The Rice-Advice research shows that adoption decisions are significantly influenced by training exposure. Our findings confirm that face-to-face contact with trusted extension workers builds confidence that impersonal introductions cannot replicate.

Second, gender inequality requires active intervention. Leaving women out of technology design and training perpetuates their marginalization. The ATPS (2024) project's design-by-inclusion approach offers a model: involve women from the earliest stages, provide targeted training, and create spaces where women can participate without fear.

Third, infrastructure constraints must be addressed. Network coverage, phone charging, and affordable data are essential prerequisites for digital agriculture to reach marginalized farmers. Without them, AI tools will benefit only those already advantaged.

Fourth, cultural alignment matters. Farmers need to see how AI advice connects to their existing knowledge. Tools designed without understanding local priorities will be rejected regardless of technical sophistication, as the Uganda cassava initiative demonstrated (AI and Equality, 2025).

Limitations and Future Research

This study has limitations. It focused on one state in northern Nigeria; findings may not transfer directly to other regions. Participants were recruited through extension agents and community leaders, potentially introducing selection bias. The qualitative design prioritizes depth over breadth and cannot provide statistical generalization.

Future research should examine whether similar patterns emerge in other Nigerian regions. Longitudinal studies could track how farmers' relationships with AI tools evolve over multiple seasons. Action research could test whether design-by-inclusion approaches produce measurable improvements in adoption equity. Quantitative studies could examine whether the barriers we identified predict adoption patterns in larger samples.

7. Conclusion

Summary of Findings

This study set out to understand how smallholder farmers in rural Kaduna State experience AI-powered agricultural advisory tools. Through interviews and focus groups with 42 farmers, we generated rich accounts of initial encounters, ongoing usage patterns, and the meanings attached to algorithmic recommendations.

Adoption is not a simple yes-or-no decision. Farmers approached the technology with scepticism rooted in previous disappointments with government programs. They integrated AI recommendations alongside indigenous knowledge rather than replacing tradition. Trust developed selectively based on observed outcomes and social relationships, not technical specifications.

Barriers operated across multiple domains. Practical constraints like phone charging and network coverage limited access. Social structures, particularly gender norms, produced patterned inequalities in who could use the tool and when. Cultural concerns about abandoning tradition shaped resistance that was meaningful rather than irrational.

Gender emerged as the most consequential axis of difference. Women's access was mediated through men. Time poverty prevented training attendance. Limited decision-making authority constrained independent experimentation. These barriers reflect structural inequalities that technology distribution alone cannot overcome.

Land tenure insecurity discouraged long-term investment in following AI recommendations. Farmers who did not control their land could not risk practices that might pay off over multiple seasons. Community hierarchies shaped information flows, with elders and successful farmers serving as gatekeepers.

Three theoretical propositions emerged. Trust is relational, not technical—it flows through trusted people rather than through algorithms alone. Adoption is an assemblage, not replacement—farmers creatively combine multiple information sources rather than substituting AI for tradition. Inclusion requires structural change, not just access—providing devices and training cannot overcome underlying power relations without addressing gender, tenure, and decision-making authority.

Contribution to Knowledge

This study makes several contributions. First, it addresses a gap identified by multiple systematic reviews. Most research on AI in Nigerian agriculture focuses on technical performance or adoption rates measured through surveys. We provide rich qualitative understanding of farmers' lived experiences, explaining not just what happens but why (Kehinde & Ogundeji, 2025; Okafor et al., 2025).

Second, the study extends the understanding of gender and technology in African agriculture. The ATPS (2024) project demonstrated that inclusive design leads to higher adoption among women. Our findings show the mechanisms: women need supportive social environments, decision-making authority, and time, not just devices.

Third, the study contributes to theoretical development. The integrated framework combining Diffusion of Innovations, Technology Acceptance Model, and gender analysis finds empirical support. We add nuance by showing how social relationships, cultural meanings, and structural positions shape perceptions of usefulness and ease of use.

Fourth, the findings validate the design-by-inclusion approach developed through recent African AI research. Farmers who experienced supportive training with familiar extension workers expressed more confidence in AI tools. How technologies are introduced matters as much as what they do.

Implications for Policy and Practice

Several implications follow.

Invest in training and support, not just technology. Training significantly influences adoption. Face-to-face contact with trusted extension workers builds confidence. Training should be ongoing, not one-time events, and should reach beyond early adopters to include marginalized groups.

Address gender inequality directly. Women constitute 60 to 80 percent of agricultural labour but face persistent barriers to technology access (ATPS, 2024). Gender-responsive interventions should include training sessions scheduled when women can attend, locations accessible to women, female trainers, and content addressing women's specific needs. Women should be involved in design from the earliest stages.

Strengthen land tenure security. Farmers who do not control their land cannot invest in long-term productivity improvements. Policy reforms that strengthen tenure security, particularly for women, would enable farmers to benefit from AI recommendations requiring multi-season investments.

Build on existing social structures. Community hierarchies shape information flows. Engaging elders, religious leaders, and successful farmers as champions can accelerate diffusion. Bypassing these gatekeepers risks rejection regardless of technical merits.

Design for practical realities. Network coverage, phone charging, and affordable data are prerequisites. Tools should work offline where possible, minimize data requirements, and accommodate low digital literacy. Language options should include local languages.

Support cultural adaptation. Farmers need to see how AI advice connects to existing knowledge. Participatory design processes that treat farmers as experts in their own context can ensure tools complement rather than contradict indigenous knowledge.

Recommendations for Future Research

Future research should pursue several directions. Longitudinal studies could track how farmers' relationships with AI tools evolve over multiple seasons. Comparative research across Nigerian regions could test the transferability of findings. Action research could implement and evaluate design-by-inclusion approaches, measuring effects on adoption equity.

Quantitative studies could examine whether the barriers we identified predict adoption patterns in larger samples. Mixed-methods designs combining surveys with qualitative follow-up could provide both breadth and depth. Research on youth engagement could explore whether younger farmers experience AI tools differently.

Studies of specific applications—pest detection, weather forecasting, market linkage—could identify whether different AI tools generate different adoption dynamics. Research on data governance could examine farmers' concerns about privacy and ownership.

Concluding Reflection

Artificial intelligence will not transform Nigerian agriculture by itself. The technology works when it meets certain conditions: trusted relationships, supportive social structures, practical infrastructure, cultural alignment, and inclusive design. Without these, AI tools risk becoming technically sophisticated but practically irrelevant.

The farmers in this study were not Luddites resisting progress. They were thoughtful practitioners making careful decisions about whether and how to integrate new tools into complex farming systems. Their scepticism was wisdom born of experience with broken promises. Their selective trust was pragmatic, based on observation of what actually worked in their fields.

For AI to fulfil its potential, developers and policymakers must take farmers' perspectives seriously. This means designing with communities, not for them. It means addressing structural inequalities that limit who can access and benefit from technology. It means supporting the creative work of assemblage that farmers already do, rather than demanding they replace their knowledge with algorithmic prescriptions.

The goal should not be technology adoption for its own sake. The goal should be technology that serves human flourishing—that supports farmers in feeding their families, sustaining their communities, and passing on knowledge to the next generation. Achieving that requires putting farmers at the centre, not as objects of intervention but as partners in innovation.

References

African Technology Policy Studies Network. (2024). Empowering women and marginalized communities in Africa's agriculture through artificial intelligence. *ATPS*. https://atpsnet.org/empowering-women-and-marginalized-communities-in-africas-agriculture-through-artificial-intelligence/

AI and Equality. (2025). Co-creating AI for agriculture: Nigeria's Nsukka yellow pepper project. *AI and Equality Toolbox*. https://aiequalitytoolbox.com/library/co-creating-ai-for-agriculture-nigerias-nsukka-yellow-pepper-project/

AI and Equality. (2025). Design by inclusion in AI development: Uganda's cassava farming initiative. *AI and Equality Toolbox*. https://aiequalitytoolbox.com/library/design-by-inclusion-in-ai-development-ugandas-cassava-farming-initiative/

Akinola, F., Kehinde, A., & Ogunleye, A. (2025). Determinants of use of digital innovation and its impact on land acquisition and food security among farming households in Nigeria. *Scientific African,* 28, e02547. https://www.sciencedirect.com/science/article/abs/pii/S2452292925000475

Begho, T., Daubry, T. P., Irabor, A. E., & Xiao, X. (2025). A scoping review of artificial intelligence and the future of African agriculture: Opportunities, challenges, and the path forward. Advances in Agriculture, 2025, 1-9. https://doi.org/10.1155/aia/2862074

Centre for Journalism Innovation and Development. (2025). Harnessing digital innovation to achieve food security in Nigeria: MDC 2025 conference report. https://allafrica.com/stories/202511260307.html

CGIAR. (2025). Gender and plant health in Nigeria's rice systems: Evidence on gender-disaggregated constraints to the use of RiceAdvice Lite. *CGIAR Sustainable Farming Program*. https://www.linkedin.com/posts/cgiar-farming_next-tuesday-we-will-host-the-16th-gender-activity-7396864312348233728-6Lct

Eromonsele, F. (2025, November 26). MDC 2025: Experts call for localisation of digital tools to drive food security in Nigeria. *Premium Times*. https://www.premiumtimesng.com/news/top-news/838560-mdc-2025-experts-call-for-localisation-of-digital-tools-to-drive-food-security-in-nigeria.html

Kehinde, A., & Ogundeji, A. (2025). Adoption impact and heterogeneity of mobile agricultural advisory technologies among smallholder farmers in Nigeria. *Discover Agriculture*, 3(1), 251. https://link.springer.com/article/10.1007/s44279-025-00427-w

Kuhn, C., Warui, M., & Kimani, D. (2025). Imagining the future of the dairy industry: A participatory human-centred approach to policy making for rural communities in Kenya. *Journal of Human Development and Capabilities,* 26(3). https://www.tandfonline.com/doi/full/10.1080/19452829.2025.2518587

News Agency of Nigeria. (2025, October 17). AgriConnect helping small farmers move from subsistence to surplus – *World Bank. NAN*. https://nannews.ng/2025/10/17/agriconnect-helping-small-farmers-move-from-subsistence-to-surplus-world-bank/

Nganga, K. G., Grossi, A., & Wanjau, A. N. (2025). Advancing gender equity in digital agro-advisory through inclusive artificial intelligence (AI): Bias analysis and strategic recommendations from the iShamba platform. AICCRA Working Papers. https://hdl.handle.net/10568/175290

Okafor, C., Nnamdi, E., & Ibrahim, Z. (2025). An integrated approach to gender equality, diversity, and inclusion in the development of artificial intelligence tools in agriculture and the food system in Africa. AI & Society. Advance online publication. https://link.springer.com/article/10.1007/s00146-025-02722-y

Omeje, E. E., Ukwuaba, I. C., Nwangwu, K. N., Umaru, I. I., Ibe, J. C., Ume, C. O., & Offorma, T. J. (2025). Rural-urban differentials in utilisation of artificial intelligence for improved agricultural production among crop farmers in Southeast Nigeria. *Journal of Agricultural Extension*, 29(2). https://www.ajol.info/index.php/jae/article/view/294649

Owusu, S. E., Arouna, A., & Narrod, C. (2024). Is personalized better: Digital advisory and productivity differentials in rice farming in Nigeria. *CGIAR*. https://data.landportal.info/nl/node/128578

Oyekunle, R. A. (2025). Factors influencing the adoption of precision agriculture technologies for food production at the International Institute of Tropical Agriculture (IITA), Nigeria. *SD Journal*, 4(2). https://journals.ug.edu.gh/index.php/sdj/article/view/4213

Shitu, A. G., Anafi, S. K., Tulagha, I., Nain, M. S., Ojobola, F. B., Olaniyan, O., Alabi, O. O., Ayegbusi, O. O., Bamigboye, O. T., Olatunji, O. C., Fanu, A. T., Ayotunde, K. O., Makinde, O. O., Shitu, M. V., Gabriel, G. O., Dandara, G. B., Adewoyin, O. B., & Mkpado, M. (2025). Use of generative AI by small-scale farmers in Nigeria: An empirical study. *Indian Journal of Extension Education*, 61(2), 78-85. https://www.semanticscholar.org/paper/Use-of-Generative-AI-by-Small-scale-Farmers-in-An-Shitu-Anafi/63721eb4953104a4b79f55bb8fc3fde10b173b4d

Yakubu, M., Yakubu, U., Yakubu, H., & Mayun, F. A. (2024). The effective use of artificial intelligence in improving agricultural productivity in Nigeria. *Journal of Basics and Applied Sciences Research*, 2(4). https://www.ajol.info/index.php/jobasr/article/view/289161