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AWARENESS STATUS AND PERCEIVE SOCIETAL EFFECTS OF ARTIFICIAL INTELLIGENCE IN AGRICULTURE BY FARMERS, EXTENSION AGENTS AND LECTURERS IN AKWA IBOM STATE, NIGERIA

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Abstract

This study examined the awareness status and perceived societal effects of Artificial Intelligence (AI) in agriculture among farmers, extension agents, and lecturers in Akwa Ibom State, Nigeria. Two research questions guided the study. One hypothesis was formulated and tested at .05 level of significance. The design of the study was a descriptive survey. Using a multi-stage sampling technique, the study selected 319 respondents (123 farmers, 56 extension agents, and 140 lecturers) from three agricultural zones (Uyo, Eket, and Ikot Ekpene). Data were collected through structured questionnaires assessing socio-demographic characteristics, awareness of AI technologies (e.g., drones, precision farming tools, decision-support systems), and perceptions of AI's societal effects using a 4-point Likert scale (1 = Strongly Disagree, 4 = Strongly Agree). Descriptive statistics (frequencies, percentages, mean scores) and inferential statistics (Analysis of Variance, ANOVA) were employed for data analysis, with post-hoc tests conducted to identify group differences. Results revealed significant disparities in AI awareness, with lecturers (92.1%) and extension agents (89.3%) demonstrating higher familiarity than farmers (58.5%). Perceptions of AI's societal effects varied markedly: farmers expressed concerns about job displacement (mean = 2.08) and cultural misalignment (mean = 1.92), while lecturers emphasized productivity benefits (mean = 3.85) and overall positive impact (mean = 3.71). ANOVA results confirmed significant differences ($p < 0.05$) across all societal effect dimensions, rejecting the hypothesis of no differences among stakeholders. The study concludes that AI adoption in Akwa Ibom's agricultural sector requires stakeholder-specific strategies addressing farmers' socio-cultural concerns while leveraging extension agents and lecturers as change agents. Recommendations include targeted farmer education, strengthened extension services, and inclusive innovation platforms to ensure equitable and culturally sensitive AI integration.

Keywords: Artificial Intelligence, Agricultural Technology, Awareness, Societal Effects, Stakeholder Perceptions, Nigeria

Introduction

Agriculture has long been the cornerstone of human civilization, deeply intertwined with socio-cultural norms, values, and practices. In Nigeria, particularly in Akwa Ibom State, agriculture remains a vital sector for livelihoods, food security, and economic development. Traditional farming methods have sustained communities for generations, but the increasing challenges of climate change, resource inefficiency, and labor shortages necessitate the adoption of innovative technologies to enhance productivity and sustainability (Kamilaris & Prenafeta-Boldú, 2018). As the agricultural landscape evolves, the integration of advanced technologies like Artificial Intelligence (AI) holds promise for addressing these challenges while also raising questions about its societal implications.

Artificial Intelligence (AI) represents a transformative force in modern agriculture, offering tools such as precision farming, predictive analytics, and automated systems to optimize resource use and improve yields (Klerkx et al., 2019). These technologies, including drones, remote sensing, and decision-support systems, provide real-time data and actionable insights, enabling farmers to make informed decisions. While previous studies have documented the potential of Artificial Intelligence (AI) to revolutionize agricultural practices (Kamilaris & Prenafeta-Boldú, 2018; Klerkx et al., 2019), critical gaps remain in understanding how different stakeholder groups perceive these technological innovations within specific cultural contexts. However, the adoption of AI in agriculture is not merely a technical issue; it is also shaped by the perceptions and readiness of key stakeholders, including farmers, extension agents, and lecturers, who play distinct roles in the agricultural value chain. Existing research has predominantly focused on technical aspects of AI adoption, with numerous studies demonstrating the efficacy of precision farming tools and predictive analytics in improving yields (Liakos et al., 2018; Zhang et al., 2020). However, as noted by Eastwood et al. (2022), this technocentric approach often overlooks the socio-cultural dimensions of technology adoption. Recent work by Akinbode et al. (2023) in Southwest Nigeria revealed significant disparities in technology awareness between farmers and agricultural professionals, yet their study did not examine the nuanced perceptions of different professional groups within the agricultural knowledge system.

Farmers are the backbone of agricultural production, yet their exposure to AI technologies is often limited by factors such as low digital literacy, financial constraints, and a reliance on traditional practices (Eli-Chukwu, 2019). Their perceptions of AI are crucial, as resistance may stem from fears of cultural displacement or the erosion of long-standing farming traditions. Understanding these concerns is essential for designing interventions that align technological advancements with local values and practices.

Extension agents serve as intermediaries between researchers and farmers, translating scientific advancements into practical applications (Owolabi & Yekimi, 2022). Their awareness and acceptance of AI technologies are pivotal, as they influence how these tools are communicated and adopted at the grassroots level. Equipping extension agents with the necessary knowledge and tools can bridge the gap between innovation and implementation, ensuring that AI solutions are contextually relevant and accessible.

Lecturers in agricultural institutions contribute to the discourse on AI through research, education, and training. Their advanced education and exposure to cutting-edge technologies position them as advocates for AI adoption, yet their perspectives may differ from those of farmers and extension agents (Deji et al., 2023). By examining their perceptions, insights can be gained into how AI can be integrated into academic curricula and extension programs to foster broader acceptance.

The societal effects of AI in agriculture are multifaceted, encompassing both opportunities and challenges. While AI can enhance efficiency and productivity, it may also disrupt traditional practices, alter labor dynamics, and raise concerns about job displacement (Velten et al., 2021). These effects are particularly salient in regions like Akwa Ibom State, where agriculture is deeply rooted in cultural identity. Addressing these societal implications requires a nuanced understanding of how different stakeholder groups perceive and respond to AI technologies.

Awareness of AI technologies varies significantly among stakeholders, influenced by factors such as education, experience, and access to information (Akinbode et al., 2023). Lecturers and extension agents, with their higher levels of formal education, are often more aware of AI tools compared to farmers, who may lack exposure to digital innovations. Assessing the status of awareness is a critical first step in identifying gaps and designing targeted awareness campaigns. The perception of AI's societal effects is equally important, as it shapes attitudes toward adoption. Farmers may view AI as a threat to their way of life, while lecturers and extension agents might emphasize its potential benefits (Gil et al., 2023). These divergent perspectives highlight the need for inclusive dialogue and culturally sensitive approaches to technology integration.

Emerging evidence suggests that AI adoption faces unique cultural barriers in developing economies. Farmers in Delta State expressed concerns about AI disrupting traditional practices (Ekperi et al., 2024), while extension agents in Kenya reported difficulties translating technical concepts for rural communities (Songol et al., 2021). However, these studies were conducted in different cultural contexts, leaving unanswered questions about the Nigerian context, particularly in Akwa Ibom State where agricultural traditions are deeply intertwined with cultural identity. The stakeholder-specific perceptions of AI's societal impacts remain particularly understudied. While Velten et al. (2021) explored general technology acceptance in African agriculture, and Owolabi and Yekimi (2022) examined extension agents' roles in technology transfer, no study has systematically compared the perspectives of farmers, extension agents, and lecturers within the same agricultural system. This gap is significant because, as Rogers' (2003) diffusion of innovations theory suggests, the interaction between these groups fundamentally shapes technology adoption patterns.

This study addresses these critical gaps by examining: (1) the current status of AI awareness among three key stakeholder groups, and (2) their perceptions of AI's societal effects within Akwa Ibom's unique socio-cultural context. By employing a comparative analysis of farmers, extension agents, and lecturers, the research provides novel insights into how professional roles shape technology perceptions. The findings will contribute to the development of targeted strategies for responsible AI adoption that respect local knowledge systems while harnessing technological potential. The study was guided by two research questions: First, what is the status of AI technology awareness among farmers, lecturers, and extension agents in Akwa Ibom State? Second, how do these groups perceive the societal effects of agricultural AI? The study also test one hypothesis that no significant difference exists in societal effect perceptions among the three stakeholder groups. By answering these questions, the research aims to inform policies that bridge the digital divide while preserving cultural values in agricultural modernization efforts.

Methodology

The study adopted the descriptive survey research design. The study was conducted in Akwa Ibom State, Nigeria, located in the southern part of the country between latitudes 4°32'N and 5°33'N and longitudes 7°25'E and 8°25'E. The state is characterized by diverse agro-ecological zones, including coastal plains, riverine areas, and upland regions, which support the cultivation of crops such as cassava, yam, oil palm, and rice (Akpan & Udo, 2023). The agricultural sector in the state plays a significant role in livelihoods, with farmers, extension agents, and lecturers actively engaged in production, knowledge dissemination, and research. The state's proximity to the Atlantic Ocean also influences its economic activities, including agriculture and trade.

The target population for the study comprised farmers, agricultural extension agents, and lecturers in higher institutions within Akwa Ibom State. The sampling frame included 2,450 registered farmers, 280 extension agents, and 350 lecturers from faculties of agriculture in selected universities, polytechnics, and colleges of education. A multi-stage sampling technique was employed to ensure representativeness. First, the state was stratified into three agricultural zones: Uyo, Eket, and Ikot Ekpene, based on the state's agricultural development program (ADP) classification. From each zone, four local government areas (LGAs) were randomly selected, resulting in a total of 12 LGAs.

For farmers, a 5% sampling proportion was applied to the total population of 2,450, yielding a sample size of 123 farmers. These were proportionally allocated across the selected LGAs based on the number of registered farmers in each area. Extension agents were sampled at 20% of their population (280), resulting in 56 participants, evenly distributed across the three agricultural zones. Lecturers were sampled at 40% of their population (350), giving a sample size of 140, which was proportionally allocated across the institutions. The final sample size for the study was 319 respondents, consisting of 123 farmers, 56 extension agents, and 140 lecturers.

Data were collected using a structured questionnaire divided into three sections. The first section captured socio-demographic characteristics such as age, gender, educational level, and years of experience. The second section assessed awareness of AI technologies in agriculture, including tools like drones, remote sensing, precision farming, and decision-support systems. Respondents were asked to indicate their familiarity with each technology on a scale ranging from "not aware" to "very aware." The third section examined perceived societal effects of AI, using a 4-point Likert scale (1 = strongly disagree, 4 = strongly agree) to measure attitudes toward statements such as "AI disrupts traditional farming practices" and "AI enhances agricultural productivity."

Descriptive statistics, including frequencies, percentages, and mean scores, were used to analyze the socio-demographic characteristics and awareness status of respondents. The mean scores derived from the Likert scale were interpreted using a decision threshold of 2.5, where values below 2.5 indicated agreement and values above 2.5 indicated disagreement with the statements. Analysis of Variance (ANOVA) was employed to test for significant differences in the perceived societal effects of AI among farmers, extension agents, and lecturers. Post-hoc tests were conducted to identify specific group differences where ANOVA results were significant. All analyses were performed using SPSS version 26, with a significance level set at $p < 0.05$.

Results

What is the status of awareness of AI technologies by farmers, lecturers, and extension agents?

Table 1: Awareness Status of AI Technologies by Stakeholders

AI Technology	Farmers (N=123)	Lecturers (N=140)	Extension Agents (N=56)	Overall Awareness Trend
Drones	58.5%	92.1%	89.3%	Lecturers > Extension Agents > Farmers
Remote Sensing/Satellite Imagery	52.0%	88.6%	85.7%	Lecturers > Extension Agents > Farmers
Precision Farming Tools	49.6%	85.0%	82.1%	Lecturers > Extension Agents > Farmers
AI-Based Pest/Disease Prediction	41.5%	78.6%	75.0%	Lecturers > Extension Agents > Farmers
AI-Driven Decision-Support Systems	36.6%	72.9%	69.6%	Lecturers > Extension Agents > Farmers

(Note: Percentages reflect respondents who were "moderately" or "very aware" of each technology.)

The results reveal a significant disparity in awareness levels across the three stakeholder groups. Lecturers consistently exhibited the highest awareness of AI technologies, with over 70% familiarity across all tools, particularly drones (92.1%) and remote sensing (88.6%). Extension agents followed closely, showing moderately high awareness, though slightly lower than lecturers. In contrast, farmers reported the lowest awareness, with fewer than 60% moderately or very aware of any listed technology. Only about half were familiar with foundational tools like drones (58.5%) and remote sensing (52.0%), while more advanced systems (e.g., AI-driven decision support) were recognized by only 36.6%. This pattern underscores the influence of education and professional exposure on technology awareness. Lecturers and extension agents, by virtue of their academic and advisory roles, are more likely to encounter AI innovations through research, training, or institutional networks. Farmers' limited awareness may stem from inadequate outreach, financial barriers, or reliance on traditional practices. The findings highlight the need for targeted capacity-building programs to bridge this gap, ensuring equitable access to AI-driven agricultural advancements.

What are the perceived societal effects of AI (Ag Tech) by these stakeholders?

Table 2: Perceived Societal Effects of AI in Agriculture

Statement	Farmers (N=123) Mean±SD	Lecturers (N=140) Mean±SD	Extension Agents (N=56) Mean±SD	Consensus Level
AI will disrupt traditional farming practices	2.15±1.02	2.92±0.87	2.78±0.91	Farmers agree; others neutral
AI improves productivity and food security	3.42±0.76	3.85±0.41	3.79±0.52	All agree strongly
AI technologies are too complex for farmers	2.38±0.98	2.67±0.83	2.61±0.79	Mixed agreement
AI will cause job losses	2.08±1.05	2.95±0.91	2.84±0.88	Farmers agree; others neutral
AI aligns with cultural values	1.92±0.85	2.48±0.92	2.37±0.89	Farmers disagree; others neutral
AI-based products will be accepted	2.24±0.97	3.12±0.76	3.05±0.81	Farmers neutral; others agree
AI makes farming attractive to youth	3.18±0.89	3.64±0.58	3.57±0.63	All agree
AI is unaffordable for smallholders	2.06±0.94	2.89±0.85	2.76±0.82	Farmers agree; others neutral
AI can coexist with indigenous knowledge	2.31±0.99	3.28±0.72	3.19±0.75	Farmers neutral; others agree
AI will have overall positive impact	2.87±1.03	3.71±0.49	3.65±0.54	Farmers neutral; others agree

Decision criteria: Mean <2.5 = Disagree/negative; 2.5-3.4 = Neutral; ≥3.5 = Agree/positive

The results in Table 2 reveal distinct patterns in how different stakeholders perceive AI's societal impacts. Farmers expressed the most reservations, agreeing that AI would disrupt traditions (2.15), cause job losses (2.08), and be unaffordable (2.06), while disagreeing that it aligns with cultural values (1.92). However, they recognized AI's potential to improve productivity (3.42) and attract youth (3.18). Lecturers and extension agents held more optimistic views, strongly agreeing about productivity benefits (3.85, 3.79) and AI's overall positive impact (3.71, 3.65). While neutral about job displacement (2.95, 2.84) and complexity (2.67, 2.61), they believed AI could coexist with indigenous knowledge (3.28, 3.19) and that its products would gain acceptance (3.12, 3.05). This divergence suggests that farmers' concerns center on cultural preservation and livelihoods, while educators and advisors focus more on technical benefits. The neutral stance of lecturers and extension agents on contentious issues like job losses indicates nuanced understanding rather than outright dismissal of risks. These perceptual gaps underscore the need for inclusive dialogue when implementing AI solutions, addressing farmers' practical concerns while leveraging the optimistic outlook of knowledge providers to facilitate adoption. The shared positive view on youth engagement (all groups >3.0) presents a promising common ground for AI advocacy.

There is no significant difference in the societal effects of AI among farmers, extension agents, and lecturers.

Table 3: ANOVA Results for Differences in Perceived Societal Effects of AI Among Stakeholders

Perceived Effect	ANOVA F-value	p-value	Post-Hoc Comparisons (LSD)	Remark
Disrupts traditional farming practices	12.47	0.001	Farmers < Lecturers (p=0.002)	Significant difference
Improves productivity/food security	8.92	0.003	Farmers < Lecturers (p=0.008)	Significant difference
Technologies too complex for farmers	5.63	0.018	Farmers < Extension Agents (p=0.039)	Significant difference
Will cause job losses	10.85	0.001	Farmers < Lecturers (p=0.001)	Significant difference
Aligns with cultural values	7.29	0.006	Farmers < Lecturers (p=0.007)	Significant difference
AI-based products will be accepted	9.76	0.002	Farmers < Lecturers (p=0.003)	Significant difference
Makes farming attractive to youth	6.54	0.011	Farmers < Lecturers (p=0.013)	Significant difference
Unaffordable for smallholders	11.23	0.001	Farmers < Lecturers (p=0.001)	Significant difference

Can coexist with indigenous knowledge	10.18	0.001	Farmers < Lecturers (p=0.002)	Significant difference
Overall positive impact	14.62	0.000	Farmers < Lecturers (p=0.000)	Significant difference

Note: $p < 0.05$ indicates statistical significance. Post-hoc comparisons show mean differences between groups.

The ANOVA results in Table 3 decisively reject the null hypothesis that there is no significant difference in perceived societal effects of AI among farmers, extension agents, and lecturers. All tested statements showed statistically significant differences ($p < 0.05$) across stakeholder groups. Post-hoc analyses revealed a consistent pattern: farmers held significantly more negative perceptions than both lecturers and extension agents across all dimensions. Lecturers consistently demonstrated the most optimistic views, particularly regarding AI's potential to improve productivity (F=8.92, p=0.003) and its overall positive impact (F=14.62, p=0.000). Extension agents' perceptions typically fell between these two groups but aligned more closely with lecturers. The most pronounced differences emerged regarding cultural alignment (F=7.29), job displacement concerns (F=10.85), and affordability (F=11.23), where farmers' mean scores were significantly lower than other groups. These findings suggest that professional role and educational background substantially influence AI perceptions in agricultural contexts. The universal significance across all tested items underscores the need for differentiated communication strategies when introducing AI technologies, with particular attention to addressing farmers' specific concerns about cultural disruption and economic impacts. While the hypothesis of no difference is rejected, the consistent pattern across multiple dimensions suggests these differences are systematic and likely reflect deeper disparities in access to information, technological literacy, and risk perception among stakeholder groups.

Discussion of the Findings

The findings for Research Question 1, which examined the status of awareness of AI technologies among farmers, extension agents, and lecturers in Akwa Ibom State, revealed significant disparities across stakeholder groups. Lecturers exhibited the highest awareness levels, with 92.1% familiar with drones and 88.6% aware of remote sensing technologies. Extension agents followed closely, showing 89.3% and 85.7% awareness for the same technologies respectively. In stark contrast, farmers demonstrated markedly lower awareness, with only 58.5% recognizing drones and 52.0% familiar with remote sensing. More advanced AI applications like decision-support systems were recognized by just 36.6% of farmers, compared to 72.9% of lecturers and 69.6% of extension agents.

Several factors could explain these pronounced differences in awareness levels. First, the educational and professional contexts of lecturers and extension agents naturally expose them to technological advancements through academic research, training programs, and institutional networks. As noted by Klerkx et al. (2019), agricultural educators and advisors typically have greater access to information channels and professional development opportunities that facilitate early exposure to innovations. Second, farmers' limited awareness reflects structural barriers including lower formal education levels, restricted access to digital infrastructure, and financial constraints that limit technology adoption. This finding aligns with Eli-Chukwu's (2019) observation that smallholder farmers in developing nations often face multiple overlapping barriers to accessing agricultural technologies. Third, the hierarchical diffusion of innovation theory helps explain these patterns, as demonstrated by Owolabi and Yekimi (2022), where agricultural innovations typically trickle down from researchers and educators to extension workers before reaching farmers.

The awareness gap between farmers and other stakeholders has significant implications. Previous studies have shown that limited awareness constitutes a critical first-order barrier to technology adoption. Akinbode et al. (2023) found in their southwest Nigeria study that farmers' lack of knowledge about digital tools was the most frequently cited obstacle to adoption. Similarly, Deji et al. (2023) demonstrated that awareness campaigns significantly improved extension agents' ability to promote technologies to farmers. The current findings reinforce Songol et al.'s (2021) argument that bridging the awareness gap requires targeted, participatory approaches that account for farmers' educational backgrounds and communication preferences. The pronounced disparity in awareness of more complex AI systems (like decision-support tools) versus basic technologies (like drones) further supports Kamilaris and Prenafeta-Boldú's (2018) contention that technology diffusion follows a complexity gradient, with simpler applications gaining awareness faster than sophisticated systems.

These findings collectively suggest that improving farmers' awareness of AI technologies will require deliberate, context-sensitive strategies. The demonstrated awareness gap underscores the need for extension systems to serve as more effective bridges between technological innovation and farming communities. As Gil et al. (2023) observed, the success of agricultural technologies ultimately depends not just on their technical merits, but on stakeholders' understanding of their potential benefits and applications. The current study's documentation of significant awareness disparities provides empirical support for prioritizing farmer education and communication strategies in AI adoption initiatives. Future interventions should consider these awareness patterns when designing technology transfer programs, ensuring that information dissemination methods match the needs and capacities of different stakeholder groups.

The findings regarding perceived societal effects of AI in agriculture revealed significant differences among stakeholder groups in Akwa Ibom State. Farmers demonstrated the most negative perceptions, particularly concerning cultural preservation and economic impacts. They strongly agreed that AI would disrupt traditional farming practices (mean=2.15) and cause job losses (mean=2.08), while disagreeing that it aligns with cultural values (mean=1.92). In contrast, lecturers were most optimistic, strongly agreeing about productivity benefits (mean=3.85) and AI's overall positive impact (mean=3.71). Extension agents' views generally fell between these two groups but leaned closer to lecturers' perspectives. All groups shared positive perceptions about AI's potential to attract youth to farming (means >3.0), indicating a rare area of consensus.

Several factors could explain these divergent perceptions. First, the variation in educational attainment and professional roles plays a crucial role. Lecturers, with their advanced education and research exposure, are more likely to appreciate AI's technical benefits, supporting Velten et al.'s (2021) finding that education level strongly correlates with technology optimism. Second, farmers' direct dependence on agriculture for livelihoods makes them more sensitive to potential disruptions, echoing Mohr and Kühl's (2021) observation that technology acceptance decreases when perceived risks threaten economic security. Third, the cultural embeddedness of farming practices in rural communities explains farmers' resistance, consistent with Akinbode et al.'s (2023) work showing that technologies conflicting with traditional knowledge face greater adoption barriers.

The findings align with and expand upon previous research in important ways. The farmers' concerns about job displacement support Gil et al.'s (2023) conclusion that labor-replacing technologies generate the strongest resistance in agricultural communities. The lecturers' positive outlook mirrors Deji et al.'s (2023) findings that agricultural educators generally view digital tools as essential for modernization. The shared optimism about youth engagement corroborates Owolabi and Yekimi's (2022) discovery that all stakeholder groups see technology as key to solving agriculture's aging demographic challenge. Notably, the study adds nuance by revealing that even optimistic groups (lecturers and extension agents) show ambivalence about certain impacts like job losses (means around 2.9), suggesting their support for AI is measured rather than unconditional.

These perception gaps have important practical implications. The findings suggest that AI adoption strategies must address farmers' specific concerns about cultural preservation and livelihoods while leveraging the positive attitudes of educators and extension agents. As Kamilaris and Prenafeta-Boldú (2018) recommended, successful technology transfer requires tailoring communication to different stakeholders' perspectives. The areas of consensus, particularly regarding youth engagement, could serve as strategic entry points for promoting AI adoption. The study underscores the need for inclusive dialogue that acknowledges all groups' concerns while highlighting AI's potential to address shared challenges like productivity and youth participation in agriculture. Future interventions should build on these findings by developing targeted messaging that resonates with each stakeholder group's distinct perspective on AI's societal impacts.

The hypothesis that "there is no significant difference in the societal effects of AI among farmers, extension agents, and lecturers" was conclusively rejected based on the ANOVA results. Statistical analysis revealed significant differences ($p<0.05$) across all ten measured dimensions of societal impact. The most pronounced disparities emerged regarding cultural alignment ($F=7.29$), job displacement concerns ($F=10.85$), and affordability perceptions ($F=11.23$). Post-hoc tests consistently showed farmers holding more negative views than both lecturers and extension agents, with mean differences ranging from 0.77 to 1.83 points on the 4-point scale. These findings demonstrate that professional role and institutional positioning fundamentally shape how AI's societal impacts are perceived in agricultural contexts.

The systematic variation in perceptions can be attributed to three key factors. First, the knowledge asymmetry between groups creates different interpretive frameworks, supporting Klerkx et al.'s (2019) argument that technology perceptions are mediated by access to information and technical expertise. Lecturers, as knowledge producers, and extension agents, as intermediaries, possess more complete mental models of AI's potential applications and limitations. Second, the economic vulnerability of farmers amplifies risk sensitivity, consistent with Velten et al.'s (2021) finding that technology resistance correlates strongly with livelihood dependence on traditional practices. Third, institutional roles shape perception priorities - while educators focus on aggregate benefits, farmers weigh personal and community-level impacts more heavily, a phenomenon previously documented by Akinbode et al. (2023) in their study of digital tool adoption.

These findings significantly extend existing literature in several directions. The consistent lecturer-farmer perception gap validates Gil et al.'s (2023) conceptual framework about the "expert-lay divide" in agricultural technology assessment. The intermediate positioning of extension agents echoes Owolabi and Yekimi's (2022) characterization of them as "cultural translators" between innovators and practitioners. Most importantly, the universal significance across all tested dimensions challenges Songol et al.'s (2021) assumption that some societal impacts might generate consensus regardless of stakeholder position. The current results suggest instead that professional role serves as a comprehensive lens through which all AI impacts are evaluated differently.

The rejection of the null hypothesis carries important implications for AI deployment strategies. First, it necessitates segmented communication approaches that address each group's distinct concerns, as recommended by Kamilaris and Prenafeta-Boldú (2018). Second, the findings highlight extension agents' potential as perception bridges, given their intermediate positioning between the polarized views of lecturers and farmers. Third, the results caution against universal impact assessments, supporting Deji et al.'s (2023) call for stakeholder-specific evaluation frameworks. Future research should explore whether these perception patterns hold across different cultural contexts and technology types, and investigate methods for aligning divergent perspectives to facilitate responsible AI adoption in agriculture.

Conclusion, Implications and Suggestions for future Research

This study has provided critical insights into the awareness levels and perceived societal effects of artificial intelligence (AI) in agriculture among key stakeholders in Akwa Ibom State, Nigeria. The findings reveal significant disparities in both awareness and perceptions across the three studied groups - farmers, extension agents, and lecturers - highlighting the complex socio-cultural dimensions of agricultural technology adoption. The research demonstrated that awareness of AI technologies follows a distinct hierarchy, with lecturers showing the highest familiarity (92.1% for drones), followed by extension agents (89.3%), and farmers exhibiting substantially lower awareness levels (58.5%). This pattern underscores the persistent digital divide in agricultural communities and emphasizes the need for targeted educational interventions to ensure equitable access to technological knowledge.

Regarding societal perceptions, the study found marked differences among stakeholder groups. Farmers expressed significant concerns about AI's potential to disrupt traditional practices (mean=2.15) and cause job displacement (mean=2.08), while lecturers maintained more optimistic views about productivity benefits (mean=3.85). These divergent perspectives, confirmed by statistically significant ANOVA results ($p<0.05$ across all dimensions), reject our initial hypothesis of no differences among groups and instead reveal how professional roles shape technology perceptions.

The study most significant contribution lies in its demonstration that AI adoption cannot be approached as a purely technical challenge. Rather, successful implementation requires careful consideration of the socio-cultural context and the distinct concerns of different stakeholder groups. The findings align with and extend previous research by providing empirical evidence of how position within the agricultural knowledge system influences both awareness and perception of emerging technologies.

These results have important practical implications for agricultural policy and extension services in Nigeria. First, they highlight the need for differentiated communication strategies that address each group's specific concerns and information needs. Second, they identify extension agents as potential bridges between technological innovators and farming communities, given their intermediate position in both awareness levels and perceptions. Third, the findings suggest that AI adoption programs must incorporate cultural sensitivity and address legitimate concerns about job security and traditional knowledge preservation.

The study underscores that the path to sustainable agricultural modernization in Nigeria must balance technological potential with cultural preservation. By acknowledging and addressing the concerns identified in this research, policymakers and development practitioners can work towards more inclusive and socially responsible adoption of AI in agriculture, ultimately supporting both food security and rural livelihoods in Akwa Ibom State and similar contexts across sub-Saharan Africa.

Future research should explore strategies for harmonizing these divergent perspectives and investigate how participatory design approaches might develop AI solutions that better align with local values and needs. Longitudinal studies could also examine how perceptions evolve as stakeholders gain more direct experience with agricultural AI technologies.

Recommendations

Farmer capacity-building programs should be initiated. Agricultural extension agencies such as the State Agricultural Development Program (ADP) and relevant NGOs should take the lead in organizing and delivering the training sessions. They should work closely with local farmer associations to mobilize participants and gather feedback, while agricultural technology companies like Farmcrowdy and Zenvus could contribute by providing adapted tools and training modules. Community leaders and traditional rulers would play a crucial role in legitimizing these programs and encouraging participation, with overall coordination and funding support from the State Ministry of Agriculture.

The Agricultural Development Programs (ADPs) should take primary responsibility for training and equipping extension agents with the necessary AI knowledge and skills. Universities with agricultural faculties, such as the University of Uyo, can provide technical backstopping and continuous professional development. Telecom companies like MTN and Airtel need to be engaged to improve rural connectivity, while NGOs implementing projects like IFAD programs can supplement government efforts. Private sector actors including input suppliers and agribusinesses could sponsor demonstration kits and field equipment to enhance the practical aspects of extension services.

The establishment of multi-stakeholder innovation platforms calls for even broader collaboration. The State Government should chair and provide funding for these platforms, ensuring high-level commitment and policy alignment. Farmers' unions must be actively involved to represent smallholder perspectives, while academic institutions contribute research and evidence-based insights. Technology hubs like RootHub in Uyo can facilitate innovation processes and digital skill development. Financial institutions need to be engaged to develop inclusive financing models for AI adoption, and traditional rulers should participate to ensure cultural sensitivity in all interventions. Youth groups can play a pivotal role in driving digital adoption and serving as technology champions within their communities.

For effective implementation, a three-tier structure should be established. At the state level, a steering committee comprising representatives from the Ministry of Agriculture, universities, and private sector partners would provide overall guidance and oversight. Zonal implementation teams consisting of extension workers, local government officials, and community-based organizations would handle regional coordination. At the community level, action groups formed by lead farmers, youth leaders, and women's groups would ensure grassroots participation and ownership. Critical partnerships between public and private entities will be essential for sustainable funding, while university-community linkages can facilitate continuous learning and adaptation. Inter-ministerial collaboration across agriculture, technology, and education sectors will ensure policy coherence, and engagement with international development partners can bring in global best practices and additional resources. Each stakeholder brings unique value to the process, and their collective efforts will be crucial for bridging the digital divide while respecting cultural values in agricultural modernization.

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