FUDMA Journal of Agriculture and Agricultural Technology
ISSN: 2504-9496
Vol. 10 No. 3, September 2024: Pp.10-18

https://doi.org/10.33003/jaat.2024.1003.02

SOCIO-CULTURAL EFFECTS OF ARTIFICIAL INTELLIGENCE IN AGRICULTURE BY FARMERS, EXTENSION AGENTS AND LECTURERS IN DELTA STATE, NIGERIA.

EKPERI, Evelyn Emamuzo.,[1] *OWIGHO, Ogheneovo.[2] & Bishop Ochuko OVWIGHO[1]

[1]Department of Agricultural Extension & Rural Development, Faculty of Agriculture, Delta State University, Abraka, Delta State, Nigeria.
[2]Department of Agricultural Economics & Extension, Faculty of Agriculture, Delta State University of Science & Technology, Ozoro, P.M.B. 5, Delta State, Nigeria.
Corresponding Authors' Email: owighoovo@gmail.com TEL: +2348033104413
https://orcid.org/0000-0003-1411-0916

ABSTRACT

The study assessed the socio-cultural effects of AI technologies in agriculture, based on the perceptions of farmers, extension agents, and lecturers in Delta State, Nigeria. A multi-stage random sampling technique was used to select 293 respondents, comprising 40% lecturers, 20% extension agents, and 5% farmers. Data were analysed using descriptive statistics, 4-point Likert scale, and Analysis of Variance (ANOVA). The results indicated significant variance in the level of awareness; lecturers at 90.9%, followed by extension agents at 94.1%, were more aware of these AI tools, including drones, than farmers (68.2%). Thereafter, the perception about AI technology in terms of sociocultural impact also differed among these groupings. Farmers were concerned that AI would change traditional practices extensively, which is at variance with the community norm, whereas the lecturers and extension agents perceived it as something positive that should happen. Results of ANOVA Post-hoc tests revealed that farmers' perceptions differed from those of lecturers with a mean difference of -1.830, p = 0.002, and extension agents with a mean difference of -1.574, p = 0.039. This study has therefore brought to the fore that interventions should be culturally sensitive in addressing farmers' concerns if AI adoption in agriculture is to be inclusive.

Keywords: Artificial Intelligence, Socio-cultural Effects, Farmers, Extension Agents, Lecturers, Delta State

INTRODUCTION

Agriculture has long been the backbone of human civilization and has always been integral to socio-cultural norms, values, and practices. Over the last couple of decades, technology started to change the agricultural scenario, and artificial intelligence (AI) is one of the most promising innovations (Evwierhurhoma *et al*., 2024). AI in agriculture encompasses all applications related to precision farming, predictive analytics, agricultural robotics, and intelligent advisory systems. Indeed, these are the very aspects where agriculture has great room for innovation from inefficiency in resources to shortage of labour and unpredictability of climate (Kamilaris & Prenafeta-Boldú, 2018). AI-driven technologies, such as drones, remote sensing, and decision-support systems, would make data more real-time and automate complex tasks, thereby, managing resources better, in order to improve yield in a much easier way (Klerkx *et al*., 2019).

Despite all the promising benefits of AI, especially in agriculture, there would not be a complete void of challenges to the adoption of such technologies in a socio-culturally diverse region like Delta State, Nigeria. Agriculture for so many communities is much more than livelihood; it is culture passed on through generations. The introduction of such technologies into traditional systems can only build resistance to change, motivated by the fear of cultural displacement, erosion of traditional knowledge, and disturbance in the social order (Eli-Chukwu, 2019). Farmers see these technologies as tools that would favour efficiency over cultural values and alienate older and traditionally rooted communities in conventional farming practices (Velten *et al*., 2021).

Delta State presents a particular case study in which such dynamics can be explored as it is, one of the Niger Delta States of Nigeria, is wrapped in a rich culture, its economy to a large extent is dependent on agriculture. Farmers, extension agents, and agricultural lecturers are population that hold different positions in the value addition chain. Farmers are the backbone of agricultural production, but they don't have much exposure to newer technologies due to various barriers in terms of low digital literacy and financial constraints. Extension agents act as an intermediary to translate scientific advancements into practical applications, while lecturers contribute through research and training on cutting-edge technologies (Owolabi & Yekinni, 2022). Such an understanding of the interaction of stakeholders' perceptions will be important in integrating AI into the agricultural framework of Delta State.

Studies, such as those by Malabe *et al*. (2019) and Olorunfemi *et al*. (2020), have discussed how huge a role the perception of stakeholders makes towards shaping the adoption and effectiveness of AI technologies. Velten *et al*. (2021) reported that the socio-cultural acceptance of a technological innovation is an important determinant of whether agricultural innovation succeeds or fails. Similarly, Gil *et al*. (2023) have shown that the willingness of farmers to adopt AI technologies is dependent on the degree in which such technologies align with the local cultural practices and social norms.

According to Oyinbo, Chamberlin and Maertens (2020), issues such as fear of losing jobs, erosion of traditional farming techniques, and marginalization of vulnerable groups need to be addressed in order to ensure the acceptance of the technology.

According to Oyinbo, Chamberlin and Maertens (2020), and Yeh *et al*. (2021), socio-cultural effects of the adoption of AI are also closely aligned with demographic variables like age, gender, education, and experience. For instance, the younger the farmer, the more they are likely to be open toward the acceptance of new technologies. Vice versa, older farmers may look at these new technologies as disruptive and not needed. Also, the gender dynamics come in for instance, where more barriers to access and utilization of AI technologies by women in agriculture may further increase the existing inequalities Owigho *et al* (2024). The educational level and experience contribute to creating perceptions, too; with more education, a lecturer and extension agent are capable of recognizing the benefits that can be argued for the adoption of AI, while farmers without a high level of formal education may not possess enough knowledge or confidence to show an interest in these technologies.

Several studies have also established that AI enhances efficiency in agriculture, decreasing labour intensity while improving the quality and quantity of agricultural outputs. For instance, Klerkx *et al*. (2019) and Akinbode *et al*. (2023) have identified a possible role of AI in precision agriculture: through satellite imagery and machine learning algorithms, interventions have been better targeted with the apparent use of resources for improving productivity. Furthermore, Marr (2018) has identified how intelligent advisory systems are useful to farmers in real-time site-specific advisories about pest control, irrigation, and market trends.

To this end, this paper addresses the socio-cultural perceptions of AI adoption by farmers, extension agents, and lecturers in Delta State through the lens of awareness, demographic features, and perceived impacts, presenting key drivers of stakeholders' attitudes toward AI. Targeted at the socio-cultural obstacles to AI adoption, this study provides insights on how these technologies may be attuned to values and customs that the locals hold dear.

Objectives of the Study

The specific objectives are to:

i. describe the socioeconomic characteristics of farmers, extension agents and lecturers in the study area
ii. examine the awareness status of AI (Ag Tech) technologies by farmers, extension agents and lecturers in the study area
iii. determine the perceived socio-cultural effects of AI (Ag Tech) technologies by farmers, extension agents and lecturersin the study area
iv. ascertain the difference in the perceived sociocultural effects of AI (Ag Tech) on agriculture among farmers, extension agents and lecturers.

METHODOLOGY

The study area is Delta State, Nigeria. Delta State is located in the southern part of Nigeria, between approximately 5.5°North to 6.5°North latitude and 5.5°East to 6.5°East longitude (Soremekun & Fagbohunka, 2020). It borders Edo State to the north, Ondo and Ekiti States to the west, the Gulf of Guinea to the south, and Anambra, Imo, and Rivers States to the east. Delta State covers an area of some 17,698 square kilometres or 6,832 square miles. The topography has coastal plains, riverine areas along the Niger Delta, and upland regions (Eromedoghene & Owigho 2023). The geographical diversity helps the State in agricultural enterprise with oil palm, cassava, yam, rice, rubber, and vegetables growing (Njoku, 2017). Being closest to the Gulf of Guinea at that position exposes the area with access to the Atlantic Ocean for proper conduct of maritime as well as trading activities. In Delta State, the agricultural sector plays a leading role in livelihood as the farmers, agricultural extension workers, and lecturers involved are actively taking part in this vital activity of production, dissemination, and imparting of knowledge and learning in agricultural pursuits. Furthermore, the State's oil and gas resources contribute to its economy, shaping the socio-economic dynamics and technology (Onwumere, 2019).

Sample size and Sampling Technique

The target population was made up of extension agents, farmers and lecturers in the faculty of agriculture in various higher institutions in Delta State. It included 329 agriculture lecturers, 256 extension agents, and 2,190 registered farmers. The sampling procedure used to select the sample size of 293 involved a stratified sampling method with proportional allocation across higher institutions, agricultural extension agents, and arable crop farmers as shown in Table 1. Each stratum was assigned a specific sampling percentage based on its population size to ensure fair representation. For higher institutions, 40% of the population (329 lecturers in the faculty of agriculture) was sampled, resulting in a sample size of 132 lectures, which was proportionally distributed among the ten institutions. Agricultural extension agents were sampled at 20% of their population (256 extension agents), yielding 51 participants, proportionally allocated across three agricultural zone which are Delta Central, Delta North, and Delta South. Arable crop farmers formed the largest stratum, with a total population of 2,190 registered farmers from randomly selected communities. A smaller sampling proportion of 5% was applied to this group due to its size, resulting in a sample size of 110 farmers. Proportional allocation ensured that each community contributed to the sample based on its population size, ensuring that areas such as Warri South, Ika North East, and Ughelli North were appropriately represented. By using different sampling percentages, the procedure accounted for variations in population sizes and the relative importance of each group in the study. The final sample size of 293 was obtained by summing the samples from all three strata: 132 from higher institutions, 51 from agricultural extension agents, and 110 from arable crop farmers. This stratified sampling approach ensured that all relevant subgroups were adequately represented, reflecting the diversity of the population. The method also balanced resource constraints with the need for accuracy, making the sample both manageable and representative for the research objectives.

Table 1: Sample size distribution

Higher Institutions			**Population**	**40% Population Sampled**
Nigerian Maritime University, Okerenkoko			17	7
Delta State University (DELSU), Abraka			63	25
Dennis Osadebay University, Asaba			51	20
Delta State University of Science and Technology, Ozoro			20	8
University of Delta, Agbor			55	22
Edwin Clark University, Kaigbodo			13	5
Delta State Polytechnic, Ogwashi-Uku			22	9
College of Education (Technical), Asaba			47	19
College of Education, Warri			26	10
Delta State College of Physical Education, Mosogar			15	6
Total			**329**	**132**
Agricultural Extension Agents			**Population**	**20% Population Sampled**
Delta Central (5 blocks)			96	19
Delta North (5 blocks)			103	21
Delta South (3 blocks)			57	11
Total			**256**	**51**
Agricultural Zones	**Local Government Area**	**Communities**	**Total number of registered arable crop farmers**	**5% Population Sampled**
Delta South	Warri South	Ubeji	235	12
		Warri	280	14
	Patani	Okoloware	140	7
		Oporoza	125	6
Delta North	Ika North East	Owa Alero	165	8
		Mbiri	195	10
	Oshimili North	Ogwashi Ukwu	135	7
		Ugbolu	205	10
Delta Central	Ughelli North	Ejekota	200	10
		Eboh	130	7
	Sapele	Sapele	220	11
		Amukpe	160	8
Total			**2190**	**110**
Grand total			**2,775**	**293**

Method of Data Analysis

Data were analysed by use of descriptive and inferential statistics. Objective (i) and (ii) were achieved using frequency counts and percentages. Objective (iii) was achieved using mean derived from a 4-point Likert type scale, while Objective (iv) was achieved using Analysis of Variance (ANOVA).

RESULTS AND DISCUSSION

Socio-economic characteristics of respondents

Various socio-economic characteristics among respondents in this study, as shown by Table 2, form varied demographics that influence perceptions against or for AI technologies in agriculture. Specifically, the gender representation in the study was generally divided between male and female; males constituted 51.8% of the farmers and 52.3% of the lecturers, while extension agents showed a slight female majority (52.9%). This balance supports the fact that more females are taking up male-dominated agricultural duties, and also supports findings by Akinbode *et al*. (2023), which indicated no significant effect of gender on the adoption of digital agricultural applications. The mean age for the respondents was 39 years for farmers and 41 and 37 years old for lecturers and extension agents, respectively. Also, age variability may affect the openness to technology, in particular, a higher percentage of lecturers above 43 years (37.1%), which agrees with previous literature where young people are easily adaptable to technology (da Silveira *et al*., 2023).

Table 2: Socio-economic characteristics of respondents

Variable	Farmers (N=110)	Lecturers (N=132)	Extension agents (N=52)	Remarks
Sex				
Male	57 (51.8)	69 (52.3)	24 (47.1)	Female
Female	53 (48.2)	63 (47.7)	27 (52.9)	dominated
Mode	Male	Male	Female	
Age (years)				
20 – 25	14 (12.7)	6 (4.5)	4 (3.0)	Highest age
26 – 31	23 (20.9)	18 (13.6)	11 (8.3)	Lecturers
32 – 37	21 (19.1)	18 (13.6)	9 (6.8)	
38 – 43	22 (20.0)	41 (31.1)	13 (9.8)	
Above 43	30 (27.3)	49 (37.1)	14 (10.6)	
Mean	39 years	41 years	37 years	
Marital status				
Single	47 (42.7)	24 (18.2)	13 (25.5)	Dominated by
Married	42 (38.2)	94 (71.2)	31 (60.8)	married
Divorced	7 (2.4)	8 (6.1)	2 (3.9)	
Separated	10 (3.4)	2 (1.5)	2 (3.9)	
Widowed	4 (1.4)	4 (3.0)	3 (5.9)	
Mode	Single	Married	Married	
Educational level				
No formal Education	10 (9.1)	0 (0.0)	0 (0.0)	Formal
Primary	11 (10.0)	0 (0.0)	0 (0.0)	education
Secondary School	33 (30.0)	0 (0.0)	4 (7.8)	
NCE/OND	16 (14.5)	0 (0.0)	12 (23.5)	
BSc/HND	29 (26.4)	38 (28.8)	27 (52.9)	
M.Sc.	9 (8.2)	51 (38.6)	7 (13.7)	
PhD	2 (1.8)	43 (32.6)	1 (2.0)	
Mode	Secondary School	M.Sc.	BSc/HND	
Working experience (years)				
1 – 5	47 (42.7)	37 (28.0)	14 (27.5)	
6-10	21 (19.1)	55 (41.7)	25 (49.0)	
11-15	10 (9.1)	16 (12.1)	6 (11.8)	11.0 years
Above 15	32 (29.1)	24 (18.2)	6 (11.8)	
Mean	14 years	11 years	9 years	
Religion				
Christian	95 (86.4)	118 (89.4)	41 (80.4)	Christianity
Moslem	7 (6.4)	10 (7.6)	7 (13.7)	
African Traditional Religion	3 (2.7)	1 (0.8)	0 (0.0)	
None	5 (4.5)	3 (2.3)	3 (5.9)	
Mode	Chrisian	Christian	Christian	

Note: figures in parentheses () are percentages

The marital status showed sharp differences between the groups. Majority (71.2%) of the lecturers and extension agents (60.8%) were married, while quite a good number of farmers were single (42.7%). According to Deji *et al*. (2023), married respondents are likely to be more open to AI technologies because of their perceived stability and professional orientation. Education also showed some significant difference among the groups, with 49.1% of farmers having secondary education, lecturers predominantly holding M.Sc. Most of them have degrees, while a majority of the extension agents hold B.Sc. or HND qualifications. The higher educational attainment among lecturers and extension agents is likely to provide them with the skills and knowledge to appreciate the benefits accruable from AI. In this regard, Carrer *et al*. (2022) found that advanced education positively influences technology adoption in agriculture.

The addition of experience and religion brought other dimensions to the demographic profile whereby farmers had an average working experience of 14 years, followed by 11 years for lecturers and 9 years for extension agents, which could lead to reliance on traditional methods and skepticism towards new technologies. This is consistent with Sibuea *et al*. (2023), who noted that a great deal of experience may negatively affect the adoption of technology unless substantial benefits are perceived. Christianity was the predominant religion across all groups, providing a shared cultural framework that may subtly influence technology perceptions. Yeh *et al*. (2021) emphasize that cultural factors, including religious homogeneity, can shape how communities engage with innovations like AI. This uniformity offers a cohesive cultural backdrop for addressing barriers to technology adoption.

These findings have further stressed the need to close the gaps in farmers', lecturers', and extension agents' awareness of AI technologies. Actually, this will be closed by many approaches: training programs, digital tools at their disposal, or even financial incentives to make technology adoption sustainable. Extension services and farm organizations must, therefore, play active roles in showcasing the practical uses of such technologies to farmers and ensuring that these are appropriate for local needs and contexts. With the right intervention, AI technologies have immense potential to improve agricultural productivity, sustainability, and livelihoods in Delta State.

Table 3: Status of awareness of AI technologies by farmers, lectures and extension agents

Item	Farmers (N=110)	Lecturers (N=132)	Extension agents (N=52)	Remarks
Remote Sensing	59 (53.6)	106 (80.3)	42 (82.4)	More E.A and Lect.
Satellite Imagery	59 (53.6)	109 (82.6)	47 (92.2)	More E.A and Lect.
Drones	75 (68.2)	120 (90.9)	48 (94.1)	More E.A and Lect.
Precision Farming Tools	73 (66.4)	117 (88.6)	46 (90.2)	More E.A and Lect.
Crop Monitoring Systems	70 (63.6)	106 (80.3)	44 (86.3)	More E.A and Lect.
Predictive Analytics	48 (43.6)	84 (63.6)	35 (68.6)	More E.A and Lect.
Chatbots and Virtual Assistants	47 (42.7)	82 (62.1)	38 (74.5)	More E.A and Lect.
Decision Support Systems	54 (49.1)	84 (63.6)	34 (66.7)	More E.A and Lect.
Machine Learning-based Pest and Disease Identification	64 (58.2)	88 (66.7)	36 (70.6)	More E.A and Lect.
Smart Farming Equipment	72 (65.5)	95 (72.0)	38 (74.5)	More E.A and Lect.
Blockchain Technology for Supply Chain Management	73 (66.4)	102 (77.3)	43 (84.3)	More E.A and Lect.
Climate Prediction Models	86 (78.2)	115 (87.1)	47 (92.2)	More E.A and Lect.

Note: figures in parentheses () are percentages, E.A = Extension Agents, Lect. = Lecturers

Perception of socio-cultural effects of AI (Ag Tech) by farmers, lecturers and extension agents

Results in Table 4 shows the perceived socio-cultural effects brought about by AI (Ag Tech) on agriculture, as perceived by farmers, lecturers, and extension agents in Delta State, Nigeria. The results show divergent and sometimes contrasting perceptions among the groups, which highlight the nuanced nature of the impacts of AI technologies on traditional agricultural practices and community values. For example, the mean score among farmers of 2.18 reflects that they agree to the statement that AI will disrupt farming and cropping systems as it is, while in contrast, lecturers and extension agents had mean scores much closer to the decision threshold of 2.5, reflecting caution or uncertainty. This is consistent with the more educated and technologically savvy groups being cautious, as Gil *et al*. (2023) pointed out that the integration of AI technologies into already existing systems could result in conflicts and thus create barriers to adoption. This cautious approach would, therefore, be indicative of a more considered approach to the challenges AI may pose to established farming methods.

The perception that AI affects community norms and values was agreed upon by all groups, with mean scores below 2.5, showing consensus. This finding corroborates Akinbode *et al*. (2023), who stated that small-scale farmers often resist digital technologies out of fear of cultural displacement and disruption of traditional practices. These are not unwarranted concerns, since the adoption of AI in agriculture could alter long-standing social structures and practices in-situ in rural communities. Yet, divergence becomes apparent in the perception of AI's influence on youth. Whereas the lecturers and extension agents disagreed with the statement that AI would result in lazy youth, reflected in mean scores of 2.56 and 2.57, respectively, farmers agreed. This contrast underlines different understandings of how AI may influence labour dynamics and societal values. According to Mohr and Kühl (2021), societal fears about AI diminishing the value of human labour are substantial, especially among farming populations.

Another important dimension of the socio-cultural effects of AI is the belief that farmers, regardless of their educational level, cannot cope with AI technologies. Farmers agreed to this view, as evidenced by the mean of 2.34, while lecturers and extension agents had a slightly higher mean score of 2.69 and 2.63, respectively, indicating partial disagreement, hence revealing the continued challenge of technical literacy and capacity building in rural areas. As such, Carrer *et al*. (2022) noted that education and technical support are required for the successful adoption of precision agricultural technologies, an observation underlining the need for targeted interventions in these areas. There was further consensus that AI technologies may conflict with local cultural practices, since all groups reported mean scores below 2.5. This consensus is further aligned with Songol *et al*. (2021), who observed that digital tools are normally at odds with the established ways of farming; hence, there may be resistance from communities with high cultural attachment.

The social acceptability about AI was perceived differently among all groups; farmers perceive it as largely unacceptable, hence their mean of 2.39, while lecturers somewhat disagreed with this precept, 3.00, and extension agents were almost undecisive, while a mean score of 2.78 has been obtained from them. This divergence suggests that while some groups recognize something of the potential of AI, others remain skeptical, fueled by fears of job loss and erosion of traditional roles. Meher (2023) also obtained a mixed reaction to AI from university educators to further press the complexity of public perception. A shared sentiment across all groups, however, was the general dislike for AI-based agricultural products, with mean scores below 2.5. Farmers, instructors, and extension agents were wary of the perceived impacts AI-driven agriculture could have on job loss and disruption to established practices. Deji *et al*. (2023), in their study, recorded a similar kind of apathy towards the adoption of AI in agriculture, despite growing awareness of its potential benefits.

The extreme view of AI as a "devil's plan" to dominate the world was also rejected across the board, with farmers at 1.85, lecturers at 1.73, and extension agents at 1.67. This tends to suggest that while respondents are worried about the socio-cultural implications of AI, they still view it rationally as a technological tool rather than as some kind of evil force. This is contrary to alarmist perspectives that may exist within popular discourse. In fact, Yeh *et al*. (2021) identified the same: although people appreciate the risks associated with AI, they generally do not embrace apocalyptic or conspiratorial views about AI. Altogether, these findings show the complexity of integrating AI in agricultural process that depends mainly on socio-cultural factors influencing the adoption and acceptance of such technologies. Tailored approaches that address these concerns while leveraging the potential benefits of AI could help mitigate resistance and enhance its integration into agricultural systems.

Table 4: Perceived socio-cultural effect of AI (Ag Tech) by farmers, lectures and extension agents

Perceived socio-cultural effect of AI (Ag Tech)	**Farmers (N=110)**	**Lecturers (N=132)**	**Extension agents (N=52)**	**Remark**
	Mean± Std. Dev.	**Mean± Std. Dev.**	**Mean± Std. Dev.**	
The AI (Ag Tech) will disrupt the farming and cropping system	2.18±1.05	2.55±1.00	2.73±0.96	Only farmers agreed
AI (Ag Tech) will affect the norms and value of our people	2.21±0.99	2.37±0.79	2.43±0.83	All agreed
AI (Ag Tech) will make the youths to be lazy	2.49±1.09	2.56±0.93	2.57±0.81	Only farmers agreed
Farmers cannot cope with AI (Ag Tech) despite their level of education	2.34±1.07	2.69±0.97	2.63±0.82	Only farmers agreed
AI (Ag Tech) is against the culture of the people	1.98±0.89	2.30±0.96	2.33±0.97	All agreed
AI (Ag Tech) is not socially acceptable	2.39±1.12	3.00±0.73	2.78±0.70	Only farmers agreed
Many farmers will dislike agricultural products from AI (Ag Tech)	2.13±0.97	2.18±0.73	2.00±0.75	All agreed
AI (Ag Tech) is devils' plan to rule the world	1.85±1.05	1.73±0.85	1.67±0.82	All agreed
Grand Mean	**2.20**	**2.42**	**2.39**	

Decision criteria: mean <2.5 is agreed; mean ≥2.5 is disagreed

Difference in socio-cultural effects of Ag Tech AI across farmers, extension agents and lecturers

The results for the sociocultural effect of Ag Tech AI on farmers, extension agents, and lecturers was achieved using ANOVA. The ANOVA results in Table 5 indicate a statistically significant difference regarding the perceived sociocultural effects of AI (Ag Tech) with F = 5.362, p = 0.005. This finding agrees with Velten *et al*. (2021), who also showed that the perception of Ag Tech AI differed into different groups, especially in its sociocultural impacts. While farmers' attitudes are generally negative regarding Ag Tech AI, that of lecturers is normally more positive due to perhaps the broader awareness of technological changes and knowledge about its theoretical impacts. The extension agents fall between both groups, though their perceptions would lean more toward those from farming communities, probably out of direct involvement with farmers. This aligns with findings by Kamilaris and Prenafeta-Boldú (2018), who noted that educational and professional backgrounds significantly influence perceptions of agricultural innovations. Surprisingly, there was no significant difference in the perception between lecturers and extension agents, with a mean difference of 0.257 (p = 0.728), hence indicating that while both might have a more informed view about Ag Tech AI than farmers, their views do not differ from each other. This is arguably because lecturers and extension agents tend to be more educated, and most are exposed to technologically advanced facilities compared to the general population of farmers. This agrees with Abdulkareem *et al*. (2021), who observe that the educational level and professional exposure make people moderate in their perceptions concerning the impact brought about by the technologies in agriculture.

Results from ANOVA and the Post Hoc tests prove that there is a perceived difference in the sociocultural impact that Ag Tech AI has induced among farmers, extension agents, and lecturers. These findings indicate that efforts to promote Ag Tech AI in agricultural practices should be cognizant of these differences in perception, especially among farmers, who seem more skeptical of its sociocultural impacts. This is in line with general literature, for example the studies by King (2017), that call for a framing of agricultural technologies in terms of the preoccupations and cultural context particular to various groups of stakeholders.

Table 5: ANOVA showing perception of sociocultural effects of Ag Tech AI within farmers, extension agents and lecturers

ANOVA					
	Sum of Squares	**Df**	**Mean Square**	**F**	**Sig.**
Between Groups	214.941	2	107.470	5.362	0.005
Within Groups	5812.609	290	20.043		
Total	6027.549	292			

Post Hoc Tests (LDS)				
Category	**Category**	**Mean Difference**	**Std. Error**	**Sig.**
Farmers	Lecturers	-1.830***	0.578	0.002
	Extension agents	-1.574**	0.758	0.039
Lecturer	Farmers	1.830***	0.578	0.002
	Extension agents	0.257	0.738	0.728
Extension agents	Farmers	1.574**	0.758	0.039
	Lecturer	-0.257	0.738	0.728

*** and ** mean is significant at the 1% and 5% level respectively

CONCLUSION AND RECOMMENDATIONS

AI technologies in agriculture create both opportunities and challenges for Delta State while AI holds great potentials for enhancing productivity, sustainability, and decision-making, its adoption is hindered by socio-cultural concerns, especially for farmers. Farmers consider AI as a threat to traditional practices and community values; therefore, any approach aimed at diffusion of technology should be culturally sensitive. Extension agents and lecturers are more open to AI because of their higher education and exposure, realizing the benefits that it can bring. These very significant differences across the aforementioned groups is a pointer to the need for an understanding of the concerns specific to each stakeholder in any effort toward inclusive and effective AI integration in agriculture. The following recommendations are made based on the findings:

i. Practical training sessions on the use of AI tools in crop monitoring, pest control, and climate prediction should be imparted to farmers through agricultural extension agents, agricultural research institutes, and NGOs with a view to enhancing the technical capacity and awareness of farmers about the benefits of AI.
ii. Support for community meetings and discussions through community leaders, extension agents, and government agencies to assuage fears of cultural displacement by describing the ways in which AI technologies can augment rather than supplant traditional farming practices should be encouraged by all stakeholders.
iii. Equipping extension agents with appropriate AI tools and training by agricultural training organizations, government agencies, and private technology providers so that they act as effective intermediaries between researchers and farmers.
iv. The governments, financial institutions, and NGOs should facilitate the introduction of subsidy programs, loans at low interest, or grants to render these AI technologies affordable and accessible for the smallholder farmers.

v. Policy-makers should ensure, through agricultural unions and academic institutions, the introduction and implementation of policies promoting the application of AI in agriculture but also safeguard traditional knowledge, cultural heritage, and using these technologies equitably.

REFERENCES

Abdulkareem, S. A., Misra, S., Kumar, P., & Alazab, M. (2021). Artificial Intelligence in Agriculture: Challenges, Solutions, and Future Directions. Sustainable Computing: *Informatics and Systems, 30*, 100479.

Akinbode, S. O., Folorunso, O., Olutoberu, T. S., Olowokere, F. A., Adebayo, M., Azeez, S. O., ... & Busari, M. A. (2024). Farmers' Perception and Practice of Soil Fertility Management and Conservation in the Era of Digital Soil Information Systems in Southwest Nigeria. *Agriculture*, *14*(7), 1182.Carrer, M. J., de Souza Filho, H. M., Vinholis, M. D. M. B., & Mozambani, C. I. (2022). Precision agriculture adoption and technical efficiency: An analysis of sugarcane farms in Brazil. *Technological Forecasting and Social Change*, *177*, 121510.

da Silveira, F., da Silva, S. L. C., Machado, F. M., Barbedo, J. G. A., & Amaral, F. G. (2023). Farmers' perception of barriers that difficult the implementation of agriculture 4.0. *Agricultural Systems*, *208*, 103656.

Deji, O. F., Alabi, D. L., Famakinwa, M., & Faniyi, E. O. (2023). Utilisation of Artificial Intelligence-based Technology for Agricultural Extension Services among Extension Professionals in Nigeria. *Journal of Agricultural Extension*, *27*(3), 81-90.

Eli-Chukwu, N. C. (2019). Applications of artificial intelligence in agriculture: A review. *Engineering, Technology and Applied Science Research*, *9*(4).

Eromedoghene, E.O. & Owigho, O (2023). Achievable rural development: scaling a useful tool in the socioeconomic status of Arable Crop Farmers in Delta State, Nigeria. International Journal of Agricultural Technology 19(1):21-36

Evwierhurhoma, F. E., Owigho, O., Akeni, T. E., Eromedoghene, E. O., O.S. Onwumere-Idolor., & Ofuoku, A.U. (2024). The Role of Artificial Intelligence and Machine Learning in Optimizing Agricultural Extension Decision Support Systems in Delta State, Nigeria. *Conference Journal of Environmental Studies, 19*(1), 1-9.

Gil, G., Casagrande, D. E., Cortés, L. P., & Verschae, R. (2023). Why the low adoption of robotics in the farms? Challenges for the establishment of commercial agricultural robots. *Smart Agricultural Technology*, *3*, 100069.

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and electronics in agriculture*, *147*, 70-90.

King, A. (2017). Technology: The future of agriculture. *Nature*, *544*(7651), S21-S23.

Klerkx, L., Jakku, E., & Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. *NJAS-Wageningen journal of life sciences*, *90*, 100315.

Malabe, K. M., Wakawa, R. C., & Gwary, M. M. (2019). A Review of agricultural intervention programs and their extension delivery system in Nigeria. *Journal of Agricultural Economics, Environment and Social Sciences*, *5*(1 and 2), 72-79.

Marr, B. (2018). How is AI used in education--Real world examples of today and a peek into the future. *Forbes, Forbes Magazine*, *25*.

Meher, V. (2023). Artificial intelligence as perceived by university teachers: an analysis in the light of demographic variables. *The Online Journal of Distance Education and e-Learning*, *11*(3).

Mohr, S., & Kühl, R. (2021). Acceptance of artificial intelligence in German agriculture: an application of the technology acceptance model and the theory of planned behavior. *Precision Agriculture*, *22*(6), 1816-1844.

Njoku, C. O. (2017). Agricultural land use pattern in Delta State, Nigeria: A geographical analysis. *Global Journal of Environmental Sciences, 16*(1), 25-36.

Olorunfemi, O. D., Oladele, O. I., & Olorunfemi, T. O. (2020). Perceived Effects of Professionalization of Extension Services by Public and Private Agents in South West Nigeria. *Journal of Agricultural Extension*, *25*(1), 59-72.

Onwumere, J. (2019). Agriculture and economic development: The Nigerian case. *African Journal of Agricultural Research, 14*(21), 964-973.

Owigho, O., Akeni, T.E., Onwumere-Idolor, O., Eromedoghene, E.O, & Ekperi, E.E. (2024). Gendered aspiration among rural youths in agriculture: Implications for food security in Delta State, Nigeria. *World Journal of Advanced Research and Reviews*, 22(03), 767–773

Owolabi, A. O., & Yekinni, O. T. (2022). Utilisation of information and communication technologies for agricultural extension service delivery in public and non-public organisations in southwestern Nigeria. *Heliyon*, *8*(9).

Oyinbo, O., Chamberlin, J., & Maertens, M. (2020). Design of digital agricultural extension tools: perspectives from extension agents in Nigeria. *Journal of agricultural economics*, *71*(3), 798-815.

Pham, H., Nong, D., Simshauser, P., Nguyen, G. H., & Duong, K. T. (2024). Artificial intelligence (AI) development in the Vietnam's energy and economic systems: A critical review. *Journal of Cleaner Production*, 140692.

Rahman, A. T. M. M., Zaman, S., and Rahman, M. H. (2020). Smart agriculture: An approach of artificial intelligence. In Advances in computer and computational sciences (pp. 607-617). Springer, Singapore.

Sibuea, F. A., Sibuea, M. B., & Harahap, G. (2023). Eksistensi Penyuluh Pertanian Dan Tingkat Adopsi Teknologi Dalam Peningkatan Produktivitas Padi Sawah di Kabupaten Deli Serdang. *JASc (Journal of Agribusiness Sciences)*, *7*(2), 175-188.

Singh, S., Farooquie, J. A., Vishwakarma, R. K., & Dash, A. (2021). Artificial intelligence (AI): Issues, applications, human-AI collaboration in agriculture, and AI regulation. *Computers and Electronics in Agriculture*, *188*, 106322.

Songol, M., Awuor, F., & Maake, B. (2021). Adoption of artificial intelligence in agriculture in the developing nations: a review. *Journal of Language, Technology and Entrepreneurship in Africa*, *12*(2), 208-229.

Soremekun, S. O., & Fagbohunka, B. S. (2020). Land use and land cover mapping using remote sensing techniques in Delta State, Nigeria. Heliyon, 6(4), e03860.

Velten, S., Jager, N. W., & Newig, J. (2021). Success of collaboration for sustainable agriculture: a case study meta-analysis. *Environment, Development and Sustainability*, 1-23.

Yeh, S. C., Wu, A. W., Yu, H. C., Wu, H. C., Kuo, Y. P., & Chen, P. X. (2021). Public perception of artificial intelligence and its connections to the sustainable development goals. *Sustainability*, *13*(16), 9165.