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Perception of Socioeconomic Effect and Constraints of Artificial Intelligence (Agricultural Technology) Performance of Agricultural Extension Agent in Delta State, Nigeria

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ABSTRACT

Artificial intelligence (AI) is taking over the different strata of life and industries, such as agriculture, to higher levels of productivity, efficiency, and decision-making with the use of smart technologies. This study evaluated the perceived socioeconomic impacts and challenges of AI on the productivity of agricultural extension agents in Delta State, Nigeria. The data was collected from 51 respondents through use of stratified random sampling technique and analyzed using descriptive statistics. The findings indicated that the majority of the extension agents saw AI as having both economic benefits and limitations. Perceived economic impacts formed the largest means of 2.89 where the respondents were most concerned with affordability with a mean of 3.14 and the redundancies that are expected to be witnessed with a mean of 2.55. Perceived barriers to AI integration mainly concerned restricted access to the internet (mean = 3.14) and lack of technical skills (mean = 3.12) with a grand mean of 2.86. From the study, it suggested that infrastructure, technical training, and policy intervention should be put in place to support AI usage in agricultural extension services.

INTRODUCTION

Artificial intelligence is taking over the different strata of life and industries, such as agriculture, to higher levels of productivity, efficiency, and decision-making with the use of smart technologies. Agricultural technology provides AI-based solutions through precision farming, automated monitoring, climate prediction, and pest and disease control, among others (Tian *et al*., 2023; Evwierhurhoma et.al., 2024). Agricultural extension services lie between the research institutions and the farmers; hence, much has to be gained in the integration of AI services within these extension services. Agricultural extension agents (AEAs) are supposed to support the adoption of AI technologies for farmers, making agriculture productive and sustainable. However, the extent of AI adoption into extension services largely depends on how AEAs perceive the AI socioeconomic effects and constraints in its performance.

Agricultural extension is fundamental in enhancing the knowledge, skill level, and increasing the use of innovative agricultural practices among the farming community. The introduction of AI-based technologies will revolutionize extension services by offering advisory support, recommending specific choices to farmers, and predictive analytics in real time. Researches show that AI-driven technologies are useful for the extension service delivery because human extension agents are few in some areas (Owigho & Eromedoghene, 2021; Sugihono *et al*., 2022). AI applications include chatbots, remote sensing, and mobile-based advisory systems. These can close the knowledge gap and enhance the decision-making power of farming practices (Deji *et al*., 2023). Nonetheless, despite all these benefits, the adoption of AI by extension agents in Nigeria is still relatively low due to several socioeconomic and infrastructural barriers.

Empirical studies have shown that the knowledge of AI technology by agricultural extension professionals is relatively high, while the level of its use is substantially low. A study on awareness and adoption of AI-based digital technology by extension professionals across Nigeria by Deji *et al*. (2023) shows that 79.4% of extension professionals were aware of AI-based digital technology, though only 55.7% had ever used it. Moreover, only 45% of the respondents reported that they disseminated innovations through AI-based technologies, while 34% demonstrated agricultural innovations through AI platforms. The study also established that while AI has made it easier for extension agents to reach their targeted audience, high costs of digital infrastructure are one major constraint to adoption.

Socioeconomic Impacts of AI on Agricultural Extension Agents Beyond Technology Adoption AI can enhance the performance of jobs, workload management, and sharing information by the extension workers. Yet, other issues like loss of jobs, overdependence on digital platforms, and disparities in the digital divide between rural and urban extension services do exist. According to Yeh *et al*. (2021), AI offers many opportunities for efficiency improvement, but stakeholders view it as a double-edged sword, offering benefits and potential risks. Similarly, Ifeanyi-obi and Ibiso (2020) noted that despite the awareness of the potentials of AI in enhancing research and accessing innovative farming techniques, non-access to ICT facilities, poor internet access, and lack of training were the limiting factors to its adoption. Agricultural extension services in Nigeria and particularly in Delta State are heavily reliant on government and donor-funded programs. The various bottlenecks exist in the adoption of AI-based Ag. Tech, such as incomplete funding and lack of sufficient technical knowledge for extension agents and farmers. Mishra, Shrivastava, and Singh (2017) mention that the knowledge gap in agriculture can be reduced through expert systems, but for that, sufficient training is needed along with digital literacy that should extend up to stakeholder engagement. The findings by Sibuea *et al*. (2023) also highlighted the critical role of extension agents in improving farmers' adoption of the technology. Absent corresponding support mechanisms, agricultural instructors and extension agents cannot succeed in incorporating AI in their work.

The integration of AI in agricultural extension services raises yet another equity issue. Assuming infrastructural deficits characterize rural areas, for example, internet connectivity or smart devices, then the majority of Nigeria's agricultural workforce, who are rural farmers, will suffer. According to research, it has been suggested that AI-based extension technologies can only be possible if they satisfy the peculiar needs of the smallholder farmer and their extension agents (Tian *et al*., 2023; Ekperi et.al 2024). Policymakers and agricultural institutions should also support enabling environments through capacity-building programs and investment in digital infrastructure. In spite of these, a number of initiatives demonstrate an increasing interest in the adoption of AI within agricultural extension. The Nigerian Agricultural Development Programme (ADP), among other agricultural innovation platforms, has begun to incorporate digital solutions to streamline the process of service delivery (Ezekiel & Akinyemi, 2022). Yet, further empirical research is needed to understand the specific socioeconomic effects and constraints affecting the performance of AI-based Agricultural Technology (Ag.Tech) in Delta State. Therefore, this study aims to evaluate the perception of socioeconomic effect and constraints of AI (Ag.Tech) performance of Agricultural Extension Agent in Delta State, Nigeria.

MATERIALS AND METHODS

Description of the Study Area

Delta State Nigeria is the study area. Delta State occupies the Southern region of Nigeria with geographical coordinates that lie between 5.5°North to 6.5°North latitude and 5.5°East to 6.5°East longitude (Ekperi *et al*., 2024). The State lies on the northern boundary of Edo State; the western boundary of Ondo and Ekiti States; the southern boundary of the Gulf of Guinea; and the eastern boundary of Anambra/Imo/Rivers States. Delta State covers a land size of about 17,698 square kilometres and is made up of plain coastal region and riverine areas in the Niger Delta Basin and up land region. The State's geographical spread and endowment boasts of various agricultural potentials that includes oil palm production, cassava, yam, rice, rubber and vegetables among other crops. Also, Delta State has a coastline on the Gulf of Guinea that grants it direct access to the Atlantic Ocean thus enable it engage in marine and trade business. The agricultural sector of Delta State supports a large part of the population with farming, agriculture extension workers as key players in farming, farming information and education (Ekperi *et al*., 2024).

Population of the Study, Sampling Technique and Sample Size

The total number of agricultural extension agents in Delta State is 256 and 20% of this population was sampled giving a total of 51 respondents. The study adopted a stratified random sampling technique in which the population is divided into groups or strata depending on their similarity in characteristics and a random sampling technique is employed on each of the strata in order to make sure that all the groups are well represented. For instance, Delta Central recorded 19 respondents, and it has 5 agricultural blocks with 96 extension agents as shown in table 1. Delta North Zonal, being the largest with 5 blocks and 103 extension agents, had 21 respondents while Delta South Zonal with 3 blocks and 57 extension agents had 11 respondents. This proportional sampling was appropriate because it ensured that all the regions in the state had an equal representation in the study, and it helped the researcher to get a variety of views regarding the effectiveness and the limitations of the AI technology to the delivery of agricultural extension services.

Table 1: Sample size distribution

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

Method of Data Collection

Data were collected by use of questionnaire. The questionnaire was converted to interview schedule in case of non-literate farmers. The questionnaires were administered by the researcher and trained enumerators. The questionnaire was divided into the following sections:

Socioeconomic characteristics of respondents.

Perceived socio-cultural effect of AI (Ag Tech).

Perceived economic effect of AI (Ag Tech).

Constraints to the use of AI.

Validity and Reliability of instruments

Content and face validity was done by the supervisor and other agricultural extension lecturers of the Department. Test-retest method was carried out on ten respondent after two weeks of the first administration to ascertain the reliability of the instrument. A Pearson Product Moment Correlation Coefficient ($r = 0.77$) showed that the instrument was reliable.

Measurement of Variables

Socio-economic characteristics of the respondents

Sex: This was measured at a nominal level of male (1), and female (0).

Age: Respondents were asked to indicate their actual age in years.

Marital status: This was measured by nominal value of single (1), married (2), separated (3), widow (4) and divorced (5)

Level of Education: Level of Education was measured by the number of years equivalent to the certificate obtained. For those who had in-complete education, the equivalent number of years when the person stopped school was taken as number of years of education. SSCE scored 12, OND (14), NCE (15), First Degree/HND (16), PGD (17), M.Sc. (18), PhD (19).

Years of experience: Respondent's years of work experience was measured in years.

Religion: Was be measured at nominal level of Christian (1), Moslem (2), African Traditional Religion (3) and None (4)

Perception of socio-cultural and economic effect of AI (Ag Tech)

The perceived socio-cultural and economic effect of AI (Ag Tech) were measured using a 4-point Likert type scale. The statements concerning the perceived socio-cultural and economic effects were constructed in negative forms. The scoring was done as follows: Strongly Agree (1), Agree (2), Disagree (3) and Strongly Disagree (4). A mean cut-off point of 2.5 and above, and below was used to dichotomise the responses into disagree and agree respectively.

Constraints to the use of AI

The constraints to the use of AI were measured using a 4-point Likert type scale. Statements regarding the various constraints to the use of AI were coded Strongly Disagree (1), Disagree (2), Agree (3), and Strongly Agree (4). A mean score of 2.5 and above and below 2.5 were used to dichotomise the responses into Agree and Disagree respectively. this was because the statements were in the positive form.

Method of Data Analysis

Data were analysed by use of descriptive such as frequency counts, percentages, means and standard deviation.

RESULTS AND DISCUSSION

Socioeconomics Characteristics of Respondents

The socioeconomic features of the respondents, as contained in Table 2, do reveal critical insights into demographics and the work environment. Accordingly, female agricultural extension agents slightly dominate (52.9%) compared to their male counterpart (47.1%), as the modal response indicates that most respondents were females. This finding agrees with related studies, such as that by Ifeanyi-obi and Ibiso (2020), which pointed out the substantial role women are playing in agricultural extension, especially in information dissemination and bridging gender-specific gaps. On age, the average age for the respondent is 37 years, with a fair share being above 43 years (10.6%), indicating relatively experienced personnel. This distribution shows a mix of youthful energy and mature experience that could potentially enhance innovation within the use of Artificial Intelligence in agricultural practices. According to Meher (2023), the finding showed that age significantly influenced AI adoption perception.

On marital status, a majority of 60.8% are married, and this could affect their stability and dedication to extension activities since married people usually have family-related reasons that drive them to perform well on the job. Educationally, a majority of 52.9% have a BSc/HND, which is the modal level of education. This high education qualification is akin to Mishra *et al*. (2017), who reported that advanced qualification extension agents suit AI-enabled tools for decision making. Moreover, the number of qualified agents up to MSc and PhD levels amounting to 15.7% combined, may reflect significant scope for practicing research-oriented applications and AI-enabled tool use in higher levels within agricultural extension.

Work experience is another critical variable; almost a half, about 49.0%, have 6-10 years of experience, while the average is nine years. With such experience, they are likely conversant with traditional methodologies for extension and thus should be well-placed to integrate AI-based technologies. Reports by Deji *et al*. (2023) indicate that this kind of professional would successfully adopt and advocate for digital technologies provided they receive relevant trainings. Of course, this shows the religious distribution of the respondents: Christian 80.4%, and these indeed reflect the demographic trends in Delta State, Nigeria. Although religion per se may not directly affect AI adoption, cultural and community influence can, and such influences bear on the acceptance and manner of implementation of technologies, as indicated by Sibuea *et al*. (2023). This dataset underlines both the readiness and constraining factors in the use of AI by extension agents to improve agricultural productivity in Delta State.

Table 2: Socioeconomics characteristics of respondents

Item	Frequency	Percent	Mean/Mode
Sex			
Male	24	47.1	
Female	27	52.9	Female
Age (years)			
20 – 25	4	3.0	
26 – 31	11	8.3	
32 – 37	9	6.8	37 years
38 – 43	13	9.8	
Above 43	14	10.6	
Marital status			
Single	13	25.5	
Married	31	60.8	Married
Divorced	2	3.9	
Separated	2	3.9	
Widowed	3	5.9	
Educational level			
Secondary School	4	7.8	
NCE/OND	12	23.5	
BSc/HND	27	52.9	BSc/HND
M.Sc	7	13.7	
PhD	1	2.0	
Working experience (years)			
1 - 5	14	27.5	
6-10	25	49.0	9 years
11-15	6	11.8	

Above 15	6	11.8	
Religion			
Christian	41	80.4	Christian
Moslem	7	13.7	
None	3	5.9	

Perceived socio-cultural effect of AI (Ag Tech) by extension agents

The findings in Table 3 show that agricultural extension agents had an inconsistent perception about the socio-cultural impact of AI in agriculture. The responses indicated that a fairly large number of them held the view that the AI (Ag Tech) would disrupt traditional farming systems (mean = 2.73) and make the youth less industrious (mean = 2.57). That the farmers will find it difficult to embrace the AI technologies because of education was also supported (mean = 2.63). Such findings point towards one being apprehensive when it comes to the farmers' and the youth readiness and flexibility towards advancement in artificial intelligence solutions. Similarly, Deji *et al*. (2023) acknowledged that despite perceiving numerous benefits in adopting AI to reach the target stakeholders, most extension professionals identified high cost of digital enablers as a critical impediment to its adoption.

On the other hand, this study affirmed that there was disagreement regarding the belief that labelled AI technologies as a contrary to norms, values or cultural practices of the locals with a mean of 2.43 and 2.33 respectively. The statement described the assertion of AI technologies as being the "devil's plan" with a mean of 1.67, or farmers would reject an AI-based agricultural product mean of 2.00, was strongly rejected. These results also point to the respondents' pragmatic and progressive attitude toward AI technologies, if their integration is not violating cultural standards. These results are in line with Yeh *et al*. (2021), who found a rational optimism of Taiwanese participants towards AI technologies and pointed out that understanding and awareness can contribute to higher acceptance without much cultural barriers.

Lastly, the total grand mean of 2.39 connotes a slight biased towards disagreeing with the negative socio-cultural impacts of AI (Ag Tech). Nevertheless, specific concerns like social acceptability (mean = 2.78) suggest that one may not be completely ready socially and infrastructurally. For instance, Sibuea *et al*. (2023) explained how several factors such as the involvement of extension agents, the idea fit and receptiveness of the innovations significantly influenced the successful use of technology among agricultural stakeholders. To reduce such worries in Delta State, stakeholders need to ensure participation and genuine discussions towards appreciating the technical advantages, as well as the socio-cultural aspects of the farming populations. This would improve the social benefits of AI usage in agriculture and make the technologies more effective in achieving their intended goals.

Table 3: Perceived socio-cultural effect of AI (Ag Tech) by extension agents

Perceived socio-cultural effect of AI (Ag Tech)	Mean	Std. Dev.	Remark
The AI (Ag Tech) will disrupt the farming and cropping system	2.73	0.96	Agreed
AI (Ag Tech) will affect the norms and value of our people	2.43	0.83	Disagreed
AI (Ag Tech) will make the youths to be lazy	2.57	0.81	Agreed
Farmers cannot cope with AI (Ag Tech) despite their level of education	2.63	0.82	Agreed
AI (Ag Tech) is against the culture of the people	2.33	0.97	Disagreed
AI (Ag Tech) is not socially acceptable	2.78	0.70	Agreed
Many farmers will dislike agricultural products from AI (Ag Tech)	2.00	0.75	Disagreed
AI (Ag Tech) is devils' plan to rule the world	1.67	0.82	Disagreed
Grand Mean	2.39		

Decision criteria: mean <2.5 Disagreed; mean ≥2.5 is Agreed

Perception of economic effect of AI (Ag Tech) by extension agents

The result in Table 4 reveals extension agents' attitudes toward AI's (Ag Tech) impact on economic aspects of farming. Extension agents acknowledged that the existence of AI, embraced in Ag Tech, may decrease the availability of manual labor (mean = 2.82), lead to redundancy (mean = 2.55), and entail high costs which are unbearable for farmers (mean = 3.14). These results support the conclusion made by Deji *et al*. (2023) and Aliyu et.al., (2024) who noted cost increase as one of the negatives associated with the use of digital technology in extension services. This implies that despite the availability of technological improvement through the implementation of AI, the socio-economy, and financial strength of the rural farmers in Delta State can limit the use of technologies. In light of this, there are essentially two recommendations that policymakers must take to address the high cost of AI tools: Subsidization of AI tools and awareness.

As seen in the study, the mean score of 3.47 depicts the likelihood of agents thinking that the use of AI might not enhance the output per hectare and even the quality of production (mean = 2.96). These perceptions contrast with studies like Sibuea *et al*. (2023), which found that the adoption of technology, such as transplanters and harvesters, significantly enhanced rice productivity. The discrepancy could stem from a lack of exposure to successful case studies or limited localized evidence supporting AI's effectiveness in precision agriculture. This calls for practical demonstrations and tailored training programs to showcase AI's potential benefits and suitability for local conditions.

Finally, though agents disagreed that AI (Ag Tech) would fail to increase farmer profits (mean = 2.18), the general apprehension of its economic impact underlines the need for capacity building and infrastructural development. In agreement with Tian *et al*. (2023), who emphasized digital tools as the future for agricultural extension, this study further supports that the integration of AI into the extension services can be a positive way to improve service delivery.

Table 4: Perception of economic effect of AI (Ag Tech) by extension agents

Perceived economic effects of AI (Ag Tech)	Mean	Std. Dev.	Remark
Farmers cannot afford the cost of purchasing AI (Ag Tech)	3.14	0.75	Agreed
AI (Ag Tech) will disrupt the availability of manual labour	2.82	0.62	Agreed
AI (Ag Tech) will not reduce drudgery associated with manual labour	2.94	0.65	Agreed
AI (Ag Tech) will not manage precision agriculture very well	3.02	0.93	Agreed
AI (Ag Tech) will not give faster production per hectare	3.47	0.64	Agreed
AI (Ag Tech) will not give better quality produce	2.96	0.79	Agreed
AI (Ag Tech) will not increase profit to farmers	2.18	0.91	Disagreed
AI (Ag Tech) will lead to redundancy and laying off workers	2.55	0.88	Agreed
Grand Mean	2.89		

Decision criteria: mean <2.5 Disagreed; mean ≥2.5 is Agreed

Constraints to the use of AI by extension agents on arable farming

Table 5 demonstrates some of the challenges encountered by agricultural extension agents in Delta State Nigeria in the adoption of AI in arable farming. The aggregate mean of 2.86 shows that the respondents still generally agree that these are constraints. Of these, the challenges are that not enough time is spent on activities that may require reliable Internet connection (mean = 3.14) and technical skills (mean = 3.12). These findings agree with the study done by Ifeanyi-obi and Ibiso (2020) who noted that internet connection and lack of ICT skills were the key challenges for the extension agents to adopt open data technologies. This is exacerbated by the prohibitive initial cost of AI (Mean = 2.94), thus there is need for capital subsidies to facilitate implementation costs of AI as underscored by Deji *et al*., (2023) who noted high cost barriers as a major impediment to use of AI in agricultural extension services.

The study showed that perceived threats to data privacy (mean = 2.63) and legal restrictions (mean = 2.76) can also be regarded as most significant limitations. Such issues raise questions about the proper use of AI technologies in agriculture across the globe as Yeh *et al*. (2021) stated that AI has two faces: the creative and the destructive. Similarly, low mean values of 2.96 and 2.57 for inadequate infrastructure and electricity supply depict systemic problems characteristic of developing countries. These infrastructural drawbacks limit the efficient use of digital technologies, which has been discussed in the literature by Sugihono *et al*. (2022) when they highlighted the necessity of stable digital environments to enhance the functions of agricultural extension officers.

In order to overcome these constraints, training as well as policy reforms must be enforced in parallel with infrastructure development. The previous studies recommend that targeted capacity building programs which are in line with Chetsumon (2005) and Oluwadiya *et al*. (2023) improves extension agent's technical competency and self-efficacy regarding AI applications. Further, based on the findings, it evident that both government and the private sector should engage in addressing what takes long to meet or develop especially in terms of meeting or providing regulations and infrastructures. The provision of highly subsidized internet, electricity, and the costs associated with AI equipment could substantially reduce these challenges hence enhancing better AI uptake and efficiency within arable farming throughout Delta State.

Table 5: Constraints to the use of AI by extension agents on arable farming

Constraints to the use of AI	Mean	Std. Dev.	Remark
Prohibitive Initial investment cost for AI is prohibitive.	2.94	0.90	Agreed
Inadequate technical expertise hinders AI implementation.	3.12	0.52	Agreed
AI requires significant infrastructure upgrades.	2.96	0.66	Agreed
Concerns about data privacy hinder AI adoption.	2.63	0.69	Agreed
Insufficient access to reliable internet connectivity.	3.14	0.72	Agreed
Regulatory barriers pose obstacles to AI deployment.	2.76	0.65	Agreed
Limited AI education hampers adoption.	2.76	0.71	Agreed
Inadequate electricity supply	2.57	0.85	Agreed
Grand Mean	2.86		

Decision criteria: mean <2.5 Disagreed; mean ≥2.5 is Agreed

CONCLUSION

The study showed that although the agricultural extension agents in Delta State acknowledge the possibilities of the use of Artificial Intelligence in enhancing service delivery and agricultural yield, the option is limited by challenges. They include high costs, poor connectivity, lack of resources such as Internet connection, weak understanding of IT, and poor support systems respectively. However, the agents revealed their openness to using AI technologies if they overcome these problems. This study shows that policies aiming at encouraging the use of AI in agriculture are required to go beyond such aspects as payment for development of AI-based solutions and introduce measures to increase the acceptance of the innovations among extension agents and farmers. Based on the findings of the study, it is hereby recommended that the Government and policy makers should ensure that extension agents and farmers have reasonable and efficient costs of internet connectivity, reliable electricity supply etc.; agricultural Institutions and Development Programs (ADPs) should arrange seminars and workshops to improve the technical know-how about AI technology of the extension agents and also develop programs that will explain how AI can help in precision farming and is financially feasible; and technology developers and private sector should work together with agricultural institutions in order to develop effective AI system that would be adapted to the needs of the local farmers.

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