USE OF SMART AGRICULTURAL TECHNOLOGIES AMONG RESEARCHERS IN AGRICULTURAL RESEARCH INSTITUTES IN OYO STATE, NIGERIA

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ABSTRACT

Smart agricultural technologies (SATs) are the emerging technologies used to improve the efficiency, productivity, and sustainability of agriculture. This study investigated the use of smart agricultural technologies among researchers in agricultural research institutes in Oyo state, Nigeria. A multistage sampling procedure was used to select a total of 165 researchers, and information on the knowledge, perception, and level of use of SATs was garnered for the study. The results were analysed using percentages, mean, Chi-square, and Pearson Product Moment Correlation. Results reveal that 66.1% of the researchers had high knowledge of the use of smart agricultural technologies such as Sensors, Drones, Artificial intelligence, Geographical Information Systems, and 58.8% had a favourable perception towards the use of smart agricultural technologies. However, the level of use of smart agricultural technologies was low for 55.2% of the researchers. The researchers' level of education (χ^2 = 8.172, p<0.05) and research institution (χ^2 = 8.579, p<0.05) had a significant relationship with the use of SATs. However, there was a significant but negative relationship between the respondents' perception and the use of smart agricultural technologies (r=-0.242, p<0.05). Although the respondents were knowledgeable about the use of SATs and had favourable perceptions towards its use but their level of use of SATs was low, and this could be due to the unavailability of these technologies in the research institutes. To promote the use of SATs by researchers, the government should provide adequate funding for the purchase and implementation of SATs to all government-owned agricultural research institutes.

Keywords: Smart agriculture, Emerging technologies, Agricultural research institute

INTRODUCTION

Smart agricultural technologies are emerging technologies such as sensors, the Internet of Things (IoT), drones, artificial intelligence, Geographical Information Systems (GIS), and digital image mapping systems designed to enhance the efficiency, productivity, and sustainability of agriculture (Gomstyn and Jonker, 2023). These technologies enable farmers and researchers to track, monitor, automate, and analyse data related to the agricultural environment. The integration of these technologies into farm operations is known as smart agriculture (Singh *et al*., 2022). This concept leverages modern technology to optimise agricultural processes, enabling the collection and analysis of data and deploying control mechanisms to improve efficiency and reduce wastage (Radhi and Abu Bakar, 2020). Among this array of technologies, sensors provide essential data for crop monitoring and optimisation, while IoT devices enable automation and remote data collection (Sadiku *et al*., 2020). Robotics plays a vital role in automating various physical tasks in agriculture, including inspection, data collection, and yield prediction (Sadiku *et al.*, 2020). Drones offer fast and efficient methods for crop scouting, treatment planning, and soil quality assessment (Mistry *et al*., 2022), while GIS, complemented by remote sensing and GPS technology, facilitates the analysis and visualisation of agricultural landscapes, land management, and crop yield estimation (Alam and Ahmed, 2008; Adekunjo *et al*., 2013).

While these technologies allow for accurate, site-specific, and real-time data collection and analysis, their adoption and availability within agricultural research institutes in Nigeria remain limited. Studies have shown that most research institutions primarily rely on basic tools such as digital pH meters, digital balances, and data analysis software, while more advanced technologies like field sensors, digital soil maps, and remote sensing software are rarely available (Ojesanmi *et al*., 2014). This limited availability has been attributed to factors such as high procurement costs, lack of technical expertise, and low institutional prioritization of smart technologies in research settings (Ojesanmi *et al.*, 2014). Despite the potential of smart agricultural technologies to revolutionise the agricultural sector, their utilisation and impact on research activities and development remain relatively unexplored, particularly in Nigeria. Against this backdrop, this study addressed the following questions:

1. What are the socioeconomic characteristics of the researchers?
2. What is the researchers' knowledge level on the use of smart agricultural technologies?
3. What is the perception of researchers on the use of smart agricultural technologies?
4. What is the level of use of smart agricultural technologies?

The hypotheses of the study are as stated:

H_01: There is no significant relationship between the selected socioeconomic characteristics of the researchers and their use of smart agricultural technologies

H_02: There is no significant relationship between the knowledge of the researchers on the use of smart agricultural technologies and the use of smart agricultural technologies.

H_03: There is no significant relationship between the respondents' perceptions of the use of smart agricultural technologies and the use of smart agricultural technologies among researchers

METHODOLOGY

The study was conducted in Oyo State, Nigeria, a predominantly agrarian state that hosts several agricultural research institutes. These include the Institute of Agricultural Research and Training (IAR&T), National Cereal Research Institute (NCRI), International Institute of Tropical Agriculture (IITA), Cocoa Research Institute of Nigeria (CRIN), Forestry Research Institute of Nigeria (FRIN), National Center for Genetic Resources and Biotechnology (NACGRAB), and National Institute of Horticultural Research (NIHORT). The target population consisted of agricultural researchers working in these institutes.

A two-stage sampling procedure was used to select 165 respondents. The first stage involved randomly selecting 60% of the seven agricultural research institutes within the state using a simple random sampling technique, resulting in the selection of four research institutes: NIHORT, IITA, CRIN, and FRIN. In the second stage, the estimated number of researchers in each selected institute was obtained from administrative staff based on institutional records. Based on this, 30% of the researchers were randomly selected from each institute, resulting in 41, 45, 41, and 38 researchers from NIHORT, IITA, CRIN, and FRIN, respectively. Structured questionnaires were used for data collection. Content and face validity were used to validate the instrument.

The variables assessed include the socio-economic characteristics, level of knowledge of the use of SATs, Perception of the use of SATs, and level of use of SATs. Knowledge of the use of SATs was measured using 32 true/false statements (true = 1, false = 0), and the mean score was used to categorize knowledge levels into high and low. Perception of the use of SATs was assessed using 26 statements, both positive and negative, rated on a five-point Likert scale. Positive statements were scored from strongly agree = 5 to strongly disagree = 1, while negative statements were reverse scored. The mean score was used to categorize perception as either favourable or unfavourable. Use of SATs was measured using 28 statements and a response scale adapted from Adekunmi and Awoyemi (2017), assessing frequency of use. Responses were scored as never = 0, occasionally = 1, and always = 2. The mean score was used to categorize the level of use into high and low. The data collected was analysed using descriptive statistical tools such as frequencies, percentages, mean, and standard deviation, and inferential statistical tools such as Chi-square and Pearson Product Moment Correlation (PPMC) were used to test the hypothesis.

RESULTS AND DISCUSSION

Socioeconomic characteristics

Table 1 shows that the mean age of researchers was 37.3 years, indicating a predominantly young and agile researchers. This is consistent with the findings of Oyetoro (2022), who reported a mean age of 33.9 years among researchers, and Abiona *et al*. (2021), who found a mean age of 36.9 years among employees in agricultural research institutes. The results also reveal that 54.5% of respondents were female, suggesting a higher female presence in research institutions. This signifies potential benefits from diverse perspectives and expertise, enhancing agricultural research outcomes through gender balance and women's inclusion. These findings contrast with those of Abanikannda *et al.* (2017) and Abiona *et al.* (2021), who reported male dominance among agricultural researchers in Nigeria.

Furthermore, the study found that 50.3% of agricultural researchers held master's degrees, indicating a well-educated cohort capable of leveraging smart agricultural technologies. This corroborates Barakabitze *et al.* (2015) observations of high literacy levels among agricultural researchers, particularly with master's degrees being the most common highest qualification.

Respondents had an average of 7.8 years of research experience, suggesting ample expertise to independently conduct research and utilise smart agricultural technologies. This aligns with the findings of Ojesanmi *et al.* (2014) and Oyetoro (2022), who reported an average of eight years of experience among agricultural researchers.

Respondents' level of knowledge of the use of smart agricultural technologies

Table 2 shows that majority (66.1%) exhibited high knowledge, while 33.9% had low knowledge. This suggests that researchers in the study area possess a strong grasp of these technologies and understand their concepts, functionalities, and potential benefits. This indicates a positive outlook for the adoption and integration of smart agricultural technologies in research practices. However, the sizable proportion with low knowledge (33.9%) highlights the necessity for targeted interventions and capacity-building initiatives. Addressing this knowledge gap will enable researchers to fully leverage these technologies, enhancing agricultural efficiency, productivity, and sustainability in the study area.

Table 1: Frequency distribution of researchers based on their socio-economic characteristics

Variables	Frequency	Percentage	Mean
Age (Years)			37.3
≤ 30	41	24.8	
31-40	75	45.5	
41-50	38	23.0	
≥ 51	11	6.7	
Sex			
Male	75	45.5	
Female	90	54.5	
Level of Education			
HND	12	7.3	
BSc/B.Tech	52	31.5	
MSc	83	50.3	
PhD	18	10.9	
Years of Experience			7.8
1-5	59	35.8	
6-10	67	40.6	
11-15	28	17.0	
16-20	5	3.0	
≥ 21	6	3.6	
Total	**165**	**100**	

Source: Field survey, 2023

Table 2: Respondents' level of knowledge of the use of smart agricultural technologies

Level of Knowledge	Frequency	Percentage	Min	Max	Mean	Std dev
Low (< mean)	56	33.9	10	32	28.26	4.04
High (≥ mean)	109	66.1				
Total	165	100				

Source: Field Survey, 2023

Respondents' perception of the use of smart agricultural technologies

Majority of agricultural researchers (97.5%) agreed that agricultural research activities are made easier with the use of these technologies. Most respondents (95.2%) agreed that smart agricultural technologies would help provide sustainable solutions to agricultural problems. The majority of 95.7% agreed that agricultural issues (such as climate change, irrigation, etc.) can be addressed using these technologies. Most of the respondents (94.3%) agreed that a lot could be achieved using these technologies. Similarly, 93.9% agreed that the data obtained from these technologies are vast and well-detailed. On the other hand, 80% of the respondents disagreed with the statement that researchers cannot achieve much when they use smart agricultural technologies, 72.2% of the respondents disagreed that these technologies could not be used for agricultural research activities, 75.1% of the respondents disagreed with the statement that data captured by these technologies are not useful for research activities. These findings suggest a strong consensus among agricultural researchers on the transformative potential of smart agricultural technologies. It also shows the widespread acceptance and confidence in SATs as essential tools for advancing sustainable agricultural research.

Respondents' level of perception of the use of smart agricultural technologies

Table 4 shows that respondents had favorable (58.8%) perceptions regarding the use of smart agricultural technologies. Recognizing the potential benefits these technologies offer to research activities. The findings suggest that smart agricultural technologies are perceived as valuable tools for enhancing the research process. This positive perception reflects a readiness to adopt and utilise these technologies if accessible.

However, a significant portion (41.2%) of respondents expressed unfavorable perceptions. This suggests that some researchers have reservations, concerns, or doubts about the effectiveness, usability, or practicality of these technologies in their specific research context. Addressing these concerns through enhanced information dissemination, training, and support initiatives could alleviate skepticism and promote greater adoption of smart agricultural technologies among this group.

Table 3: Respondents' Perception of the Use of Smart Agricultural Technologies

Perception Statements	SA (%)	A (%)	U (%)	D (%)	SD (%)
Sensors, robotics, and IoT are not applicable for agricultural research activities.	3.0	13.9	10.9	25.5	46.7
Agricultural research activities are made easier with the use of these technologies	64.8	32.7	1.8	0.6	0.0
These technologies can help address agricultural related issues (such as climate change, irrigation, etc.)	51.5	44.2	3.0	1.2	0.0
These technologies would help achieve sustainable solutions to agricultural problems.	55.8	39.4	4.8	0.0	0.0
Using these technologies can be time-consuming	4.8	15.8	9.7	43.6	26.1
The technologies facilitate the sourcing and management of information.	52.7	38.8	6.1	2.4	0.0
Researchers cannot achieve much using these technologies.	4.8	9.1	6.1	33.3	46.7
Technology guarantee efficiency.	50.3	42.4	6.7	0.6	0.0
These technologies are expensive to acquire	37.0	39.4	8.5	12.1	3.0
Robust data can be collected and analysed using smart agricultural technologies	49.1	44.2	4.8	1.8	0.0
Lack of adequate technical know-how can lead to generation of inaccurate result.	47.3	33.3	10.3	7.3	1.8
Smart agricultural technologies provide easy access to data.	42.4	50.9	4.2	2.4	0.0
Smart agricultural technologies increase the productivity of researchers	47.9	45.5	6.1	0.6	0.0
With the use of these technologies a lot can be achieved within a short time	53.9	41.2	3.0	1.8	0.0
Data captured by these technologies are not useful for research activities	10.3	9.1	5.5	32.1	43.0
Data captured by these technologies are vast and well detailed	53.3	40.6	5.5	0.6	0.0

SA – Strongly agree, A – Agree, U – Undecided, D – Disagree, SD – Strongly disagree
Source: Field Survey, 2023

Table 4: Respondents' level of perception of the use of smart agricultural technologies

Perception towards the use	Frequency	Percentage	Min	Max	Mean	Std dev
Unfavorable	68	41.2	73	124	101.97	11.58
Favorable	97	58.8				
Total	165	100				

Source: Field survey, 2023

Respondents' use of smart agricultural technologies

Table 5 shows that about one-third (33.9%) of the respondents always use Geographical Information Systems (GIS) for geographical data capture, while 30.9% always utilise the Internet of Things (IoT) for data gathering. Similarly, 30.3% always employ GIS for geographic data processing and integration, with 29.1% always using IoT for gathering environmental data. However, 41.2% of respondents occasionally use sensors for monitoring soil and climate conditions, while 38.8% occasionally utilise GIS for solving geographical issues. Additionally, 37.6% occasionally employ GIS for data processing and mapping.

These findings suggest a moderate but inconsistent pattern in the utilisation of smart agricultural technologies among researchers. While some respondents integrate these tools into their workflows regularly, many use them occasionally, suggesting varying degrees of familiarity, access, or relevance to their research focus. These findings align with those of Ojesanmi *et al*. (2014), who reported that while technologies such as GIS and GPS were widely used (60%) for generating research area maps and classifying soils, more advanced technologies like remote sensing were rarely used (1.1%). They attributed this to factors such as lack of specialist skills, software limitations, and technical complexity. Their findings also support the notion that the availability of these technologies does not guarantee their consistent usage; however, factors such as knowledge, relevance to research objectives, and institutional support all influence how frequently these technologies are used.

Table 5: Respondents' use of smart agricultural technologies

Statements	Mean	Std Dev
I use sensors to monitor soil, climate conditions and climate change	0.84	0.75
I use sensor to gather relevant data for my research activities	0.87	0.79
I use sensors with other technologies to carry out research processes	0.73	0.77
I use UAV to monitor the health and growth of vegetation	0.41	0.64
I use UAV together with sensors to assess and analyse the field for research purposes	0.48	0.75
I use robotics to collect spatial data including GPS data to help with mapping.	0.23	0.50
I use digital image mapping system to estimate soil moisture and other soil properties	0.64	0.78
I use GIS to capture geographical data	0.96	0.85
I use GIS to process geographic data and integrate it into a map	0.98	0.79
I use GIS for solving geographical problems	0.93	0.78
I use GIS for soil mapping and soil analysis	0.89	0.83
I use IoT to gather information on temperature, humidity, light and pressure levels for research purposes	0.88	0.83
I use IoT for surveying and mapping of field	0.69	0.78
I use IoT to evaluate field variables such as soil state, atmospheric conditions, and biomass of plants or animals	0.62	0.72
I use IoT to gather relevant data for research purposes	0.92	0.84

Source: Field Survey, 2023

Respondents' level of use of smart agricultural technologies

Table 6 reveals that 55.2% of the respondents had a low level of use, indicating a significant non-use of smart agricultural technologies among agricultural researchers in the study area. Conversely, 44.8% of the respondents had a high level of use, indicating a successful integration of these technologies into their research practices. While many respondents have high knowledge of how to use these technologies, their actual usage is low. This suggests that barriers beyond technical knowledge, such as inadequate institutional support, limited funding for equipment and software, poor internet infrastructure, and the absence of organisational incentives, may significantly hinder utilisation. Additionally, some researchers may not perceive these technologies as immediately relevant to their specific research objectives, especially in specializations or units where traditional methods remain dominant.

Table 6: Respondents’ level of use of smart agricultural technologies

Level of use	Frequency	Percentage	Min	Max	Mean	Std Dev
Low (< mean)	91	55.2	0	53.0	18.0	15.15
High (≥ mean)	74	44.8				
Total	165	100				

Source: Field Survey, 2023

Test of hypotheses

Table 7 reveals that the respondents' level of education ($\chi2 = 8.172$, $p < 0.05$) and research institution ($\chi2 = 8.579$, $p < 0.05$) had a significant relationship with their use of smart agricultural technologies. The statistically significant relationship suggests that these factors influence agricultural researchers' adoption and utilisation of these technologies. It implies that researchers with higher levels of education are more likely to use smart agricultural technologies. For the research institutions, the implication is that the organisational context and support provided by the research institution influence the use of smart agricultural technologies.

PPMC analysis of respondents' knowledge and use of smart agricultural technologies reveals that there is no significant relationship ($r= 0.083$, $p > 0.05$). This implies that knowledge does not necessarily lead to its practical application. Conversely, the PPMC analysis of respondents' perceptions and use of smart agricultural technologies reveals a significant negative relationship ($r= -0.242$, $p < 0.05$). Despite the favourable perceptions, usage levels remain low, indicating additional factors beyond perception affect adoption and utilisation.

Table 7: Test of hypotheses on the use of smart agricultural technologies

Variable	N	χ^2	Df	p-value
Level of education	165	8.173*	3	0.043
Research institution	165	8.579*	3	0.035
Variable	**N**	**r-value**	**df**	**p-value**
Knowledge	165	0.083	-	0.289
Perception	165	-0.242**	-	0.002

Source: Data Analysis, 2023

CONCLUSION AND RECOMMENDATION

The study revealed that agricultural researchers in Oyo State possess knowledge and hold favourable perceptions regarding smart agricultural technologies. However, their actual utilisation of these technologies remains low. The most frequently used technologies were Geographical Information Systems and the Internet of Things, primarily for data capture, processing, and environmental monitoring. This limited usage could be attributed to inadequate access and availability of these technologies within research institutes. To address this, it is recommended that the government allocate sufficient funding to agricultural research institutes for the acquisition and implementation of smart agricultural technologies. Additionally, institutes should ensure adequate infrastructure support, such as runway facilities for fixed-wing UAVs, to facilitate effective utilisation. Training, workshops, and educational resources should also be provided to enhance researchers' understanding and awareness, build technical capacity, and promote broader adoption of these technologies in agricultural research.

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