

**SOCIO-CULTURAL EFFECTS OF ARTIFICIAL INTELLIGENCE
(AI) IN AGRICULTURE BY FARMERS AND EXTENSION AGENTS
IN EDO STATE, NIGERIA**

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BENIN CITY, NIGERIA**

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**A PROJECT SUBMITTED TO THE DEPARTMENT OF AGRICULTURAL
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CERTIFICATION

This is to certify that this project work was carried out by **Emmanuel OLABAMERUN** with the matriculation number **AGR2000037** of the Department of Agricultural Economics and Extension Services, Faculty of Agriculture, University of Benin, Benin City, Nigeria.

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DEDICATION

This project is dedicated to Almighty God who saw me through my undergraduate programme in the University of Benin, by giving me the strength and the grace to strive.

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I would like to express my heartfelt gratitude to God Almighty for granting me the ability, wisdom, and knowledge to carry out this research work. His unwavering provisions have been extremely important in completing this program.

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ABSTRACT

This study examined the socio-economic effects of artificial intelligence in Agricultural by farmers and extension agents in Edo state, Nigeria. A stratified sampling procedure was used to select 131 farmers and 82 extension agents that were used for this study. The specific objectives were analyzed using descriptive statistics (frequency, percentage and mean rating) why regression analysis was used to analyze the hypothesis. Findings revealed that the majority of farmers (62.4%) and extension agents (61.7%) were male, and most fell within the economically active age range of 31–50 years. Awareness level of AI technologies was high, 74.4% and 91.7% of farmers and extension agents respectively, satellite imagery (64.0% of farmers; 75.0% of extension agents), and climate precision models (60.0% of farmers; 81.7% of extension agents). However, advanced technologies such as remote sensing recorded low adoption (8.0% of farmers; 1.7% of extension agents). Adoption levels of Artificial intelligence(AI) varied and showed mixed sociocultural reactions towards AI technologies. The regression analysis shows that most socio-economic characteristics, sex ($\beta = 0.162$; $p = 0.020$), association membership ($\beta = 0.258$; $p < 0.01$), awareness of AI ($\beta = 0.585$; $p < 0.01$), and location ($p = 0.058$) of respondents have significant influence on awareness ($\beta = 0.585$; $p < 0.01$) and adoption (Adjusted $R^2 = 0.523$) of AI technologies with some sociocultural effects. The study concludes that while awareness and partial adoption of AI technologies are increasing, full integration into agricultural practice is hindered by socio-cultural beliefs, limited infrastructure, and gaps in technical capacity. It recommends targeted capacity-building programs, culturally sensitive technology introduction strategies, and strengthened extension service delivery to enhance AI adoption without undermining local traditions.

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background of the study

Artificial intelligence is a powerful transformative force in agriculture and beyond, delivering innovative solutions to complex challenges with remarkable efficacy. AI plays a crucial role in education, with the potential to transform traditional teaching methods and aid in research. Artificial intelligence involves the creation of computers that can perform tasks requiring human intelligence, such as learning, problem-solving, decision-making, and perception. AI allows machines to process and analyze data, identify patterns, and make predictions or decisions based on that analysis. This encompasses various technologies such as machine learning, natural language processing, and data analytics.

Artificial Intelligence (AI) has the potential to revolutionize agriculture by boosting productivity, optimizing resource use, and addressing problems like low yields and climate variability (Ogunniyi and Babu, 2021). In Edo State, where farmers face resource constraints and environmental restrictions, AI-powered solutions can provide real-time crop monitoring, insect identification, and customized farming advice (Eze *et al.*, 2020). Despite these advantages, the introduction of AI also introduces sociocultural challenges. Farmers, who often lack financial resources and computer literacy, can view AI as a threat to the customs that helps to bring people together, build trust, and strengthen the

bonds within their community (Adewumi and Oladipo, 2019). Farmers may become resistant to the transition from manual, labour-intensive farming to automated systems since it may upset social norms such as group labour practices (Okunlola and Ojo, 2020). Additionally, in rural areas where agriculture is the main source of income, AI's ability to lower labour needs may make unemployment worse (FAO, 2019).

Agriculture in Nigeria heavily depends on people's livelihood, particularly in Edo State, where smallholder farmers make up the majority of the population (Oisamoje and Oisamoje, 2010). In Edo State, farming is not only an economic activity but also a sociocultural practice that is deeply rooted in traditional knowledge systems, social structures, and community identity. These traditions, which are often passed down through the generations, are a reflection of community cooperation, environmental management, and cultural heritage (Adebo, 2014). Extension workers play a crucial role in connecting farmers with scientific advancements by disseminating innovations to boost production (Akinola, 2016). However, the introduction of Artificial Intelligence (AI) technologies, such as drones, automated irrigation systems, precision farming tools, and AI-driven advising platforms, presents Edo State's agricultural sector with both revolutionary opportunities and sociocultural challenges.

The sociocultural implications of AI also include issues of equity and access. Gender differences in land ownership and financial access may limit the rate of women's adoption of AI technology in Edo State, where women make up a large portion of the agricultural workforce, thus increasing already-existing disadvantages (Ogunlela and

Mukhtar, 2009). Similar to this, the cultural value of native crop types and traditional land-use patterns, which are essential to Edo State's rural populations, may affect the standardisation of farming practices brought about by AI (Adebo, 2014). Due to the exposure to present-day technologies, extension agents who act as intermediaries of innovation may have a more favourable perception of AI than farmers who place a higher priority on tradition preservation (Akinola, 2016). According to research conducted in delta state, academics and extension professionals frequently welcome AI's promise, while farmers worry about how AI may affect their autonomy and traditional methods (Eze *et al.*, 2020).

Examining how AI integration impacts Edo State's agricultural practices and social fabric is necessary given the interaction of various sociocultural processes. Understanding the obstacles to AI adoption and making sure that technology interventions are in line with cultural values depend heavily on the opinions of farmers and extension agents (Okunlola and Ojo, 2020). By investigating the farmers and extension agent's point of view, this study aims to close the knowledge gap about the sociocultural impacts of AI in Edo State's agriculture. The purpose of this study is to educate farmers on the importance of how AI improves agricultural productivity while protecting the socio-cultural legacy of farming communities in Edo State by identifying various possibilities and constraints (FAO, 2019).

1.2 Problem Statement

Agriculture is the backbone of Nigerian economy providing food, employment, raw materials etc. Government and non-governmental agencies have been deliberately conducting research to bring out innovations that can enhance agricultural production. These innovations are disseminated to the farmers through extension personnel.

Even with all of the potential advantages of AI in agriculture, there would still be obstacles to its widespread use in places with a diverse sociocultural landscape such as Edo State, Nigeria. Agriculture for so many people is more than just a means of subsistence. It is a custom that has been passed down from one generation to another. Integration of AI technology into traditional institutions can increase resistance to change only because of the fear of cultural displacement, loss of traditional knowledge, and disruption of the social order (EliChukwu, 2019). Farmers see these technologies as tools that would prioritize productivity over cultural values and alienate older, traditionally rooted groups in traditional farming practices (Velten *et al.*, 2021).

Using Edo state as a case study, despite its rich cultural heritage, a significant portion of its economy depends on agriculture. Farmers and extension agents are people who occupy various roles in the value addition chain. Although farmers are the backbone of agricultural production, they are not often exposed to newer technologies because of a number of obstacles, including limited financial resources and low levels of digital

literacy. While farmers carry out agricultural productivity, extension agents serve as a bridge to convert scientific discoveries into real-world applications (Owolabi and Yekinni, 2022). Such an understanding of the interaction between farmers and extension agents will be important in integrating AI into the agricultural framework of Edo State.

Studies have examined how stakeholders' perceptions greatly influence the adoption and effectiveness of AI technologies by Malabe *et al.* (2019) and Olorunfemi *et al.* (2020). According to Velten *et al.* (2021), sociocultural acceptability of technological innovations plays a significant role in determining its success or failure in agriculture. Similarly, Gil *et al.* (2023) Likewise, have demonstrated that farmers' readiness to embrace AI technology depends on how well it fits with their regional social norms and cultural practices (Ekperi *et al.*, 2024).

According to Oyinbo, Chamberlin and Maertens (2020), to guarantee that the technology is accepted, problems like the fear of losing one's job, the decline of traditional farming methods, and the marginalization of vulnerable groups must be resolved.

According to Oyinbo, Chamberlin and Maertens (2020), and Yeh *et al.* (2021), demographic factors like age, gender, education, and experience are also strongly correlated with the sociocultural impacts of AI adoption. For instance, younger farmers will likely accept new technologies while older farmers may see these new technologies as disruptive and unnecessary. However, gender dynamics such as inability of women to access and use AI technologies in agriculture may further increase the existing

inequalities Owigho *et al* (2024). Experience and educational attainment also play a role in shaping perceptions; an extension agent with greater education can identify the advantages that can be made for the use of AI, whereas farmers with less formal education might not know enough or be confident enough to express interest in these technologies.

Hence, this research seeks to unravel the sociocultural effects of Artificial Intelligence (AI) in agriculture among extension agencies and farmers in Edo state, Nigeria.

Given the ground, it was therefore imperative to carry out this research with a view to providing answers to the following questions:

1. Describe the socioeconomic characteristics of farmers and extension agents in the study area
2. Examine the awareness of AI (Ag Tech) technologies by farmers and extension agents in the study area.
3. Examine the current adoption levels of AI (Ag Tech) technologies by farmers and extension agents in the study area.
4. Determine the perceived socio-cultural effects of AI (Ag Tech) technologies by farmers and extension agents in the study area.

1.3 Objective of the study

The main objective of study is to access the socio-cultural effects of Artificial Intelligence (AI) in Agriculture by farmers and extension agents in Edo state, Nigeria.

The specific objectives are to:

1. describe the socioeconomic characteristics of farmers and extension agents in the study area;
2. examine the awareness of AI (Ag Tech) technologies by farmers and extension agents in the study area;
3. examine the current adoption levels of AI (Ag Tech) technologies by farmers and extension agents in the study area;
4. determine the perceived socio-cultural effects of AI (Ag Tech) technologies by farmers and extension agents in the study area;

1.4 Justification of the study

Artificial Intelligence is transforming agriculture globally using tools like precision farming and predictive analytics to enhance agricultural productivity Klerkx *et al.* (2019) and Akinbode *et al.* (2023). However, in Edo State, Nigeria, where agriculture is deeply rooted in sociocultural norms, limited research has been conducted on the significant effects of AI on farmers and extension agents.

Therefore studying the socio-cultural effects of AI in agriculture in Edo State is vital to ensure that technology improvements correspond with local practices and needs Gil *et al.* (2023). Farmers may be against AI because they are not familiar with such innovations. Also, the region's deeply ingrained traditional farming practices may cause cultural confusion for farmers.

By mid-century, Nigeria is poised to be the world's third-most-populous country, with its population rising from about 220 million today to 400–401 million people (UNFPA, 2023). Feeding this larger population therefore requires higher agricultural production yields. Findings from this study will help to reveal the sociocultural factors that can enhance the usage of AI and its associated benefits. The study can highlight the need for tailored training programs that ensure AI tools are user-friendly and accessible while also accounting for sociocultural considerations.

This study will provide insights on how to achieve the adoption of AI technologies to fit local cultural practices. Its findings will contribute to existing literature, support policy development and offer recommendations to help farmers increase their productivity through the adoption of AI technologies brought to them by extension agents without necessarily disrupting their cultural and traditional practices.

1.5 Hypothesis of the study

H₀: There is no significant relationship between the socio-economic characteristics of respondents and their level of awareness of AI.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Theoretical Framework

The Diffusion of Innovation (DOI) theory, originally developed by Everett Rogers in 1962 and later revised in 2003, remains one of the most widely used frameworks for explaining how innovations spread within a population (Rogers, 2003). At its core, DOI posits that the adoption of new technologies or ideas is not simply a matter of technical utility but a complex social process shaped by communication, trust, and the cultural context of the adopting community. According to the theory, innovations diffuse through a social system over time via communication channels, where interpersonal networks, opinion leaders, and change agents play decisive roles in influencing acceptance (Rogers, 2003; Greenhalgh *et al.*, 2005).

The theory categorizes adopters into five groups' innovators, early adopters, early majority, late majority, and laggards each of which responds differently to new ideas based on their risk tolerance, access to information, and social positioning. In agricultural settings, innovators are often progressive farmers or digitally literate extension agents who first experiment with new tools, while laggards tend to be older, resource-constrained farmers who rely heavily on indigenous practices and peer validation (Adesina & Baidu-Forson, 1995). Understanding these adopter categories is essential in assessing the diffusion of artificial intelligence (AI) in Edo State, where variations in

literacy levels, gender roles, and socio-economic status are expected to influence adoption patterns.

DOI further outlines five perceived attributes of innovation that determine adoption: relative advantage, compatibility, complexity, trialability, and observability. Relative advantage refers to the perceived superiority of AI tools compared to existing practices, such as traditional pest control or indigenous weather prediction. Compatibility relates to how well AI aligns with farmers' cultural values, language, and indigenous knowledge systems. Complexity concerns the perceived difficulty of using AI tools, which may be heightened in Edo State due to low digital literacy among rural farmers. Trialability involves opportunities to experiment with AI tools on a limited scale, often facilitated by extension demonstrations. Finally, observability denotes the visibility of AI's benefits within the community; if farmers witness neighbours improving yields through AI recommendations, diffusion is accelerated (Rogers, 2003; Feder and Umali, 1993).

In the context of Edo State, Nigeria, the DOI framework provides a useful lens to analyse both acceptance and resistance of AI technologies among farmers and extension agents. For instance, adoption may be hindered if AI platforms are not compatible with local dialects or if they conflict with deeply held indigenous farming practices. Conversely, when AI is promoted by trusted extension agents or respected community leaders, the credibility gained through interpersonal networks can overcome resistance. Empirical evidence shows that in Nigerian agriculture, peer influence and community norms often determine whether farmers integrate new technologies into their practices, regardless of

objective benefits (Arouna *et al.*, 2021). Therefore, extension agents in Edo State act as both change agents and opinion leaders, mediating the diffusion process by contextualizing AI recommendations in culturally acceptable ways.

Furthermore, DOI emphasizes the social system as a determinant of diffusion. Edo State is characterized by communal farming practices, strong kinship networks, and respect for authority figures, all of which influence technology adoption pathways. Farmers are more likely to adopt AI tools if early adopters within their social system such as cooperative leaders or influential extension workers endorse and model their use. However, structural barriers such as gendered access to mobile devices or the cost of data services may slow adoption among vulnerable groups, particularly women and resource-poor households (Mbo'o-Tchouawou and Colverson, 2014). These socio-cultural dynamics illustrate why AI adoption cannot be understood purely in technical terms but must be situated within the lived realities of farmers and extension actors.

2.2 Conceptual Framework

The conceptual framework for this study is anchored in the Diffusion of Innovations (DOI) Theory, as developed by Rogers (2003). The DOI theory provides a robust lens for examining how new technologies spread across social systems and underscores that adoption is not merely a technical decision but a process influenced by socio-cultural norms, interpersonal networks, and institutional contexts. Central to DOI are five perceived attributes of innovations relative advantage, compatibility, complexity,

trialability, and observability which jointly determine the pace and extent of adoption (Rogers, 2003).

When applied to artificial intelligence (AI) in agriculture, these attributes take on specific socio-cultural dimensions within Edo State, Nigeria. Relative advantage reflects the perceived economic or productivity benefits of AI tools compared to traditional farming practices. For instance, farmers may evaluate AI-enabled weather forecasting or pest detection systems based on whether they yield better outcomes than indigenous knowledge systems. Compatibility involves the alignment of AI technologies with farmers' cultural values, language, and farming traditions. Technologies that do not consider local dialects, gender norms, or communal decision-making processes may face resistance despite their technical potential (Munyua, 2019). Complexity refers to the perceived difficulty of using AI systems. In Edo State, limited digital literacy, low internet penetration, and infrastructural constraints may make AI tools appear overly complex, discouraging adoption (Rose *et al.*, 2021).

Trialability is another crucial factor, highlighting the need for farmers and extension agents to experiment with AI tools on a small scale before committing fully. Demonstration plots, farmer field schools, and pilot programs facilitated by extension agents can serve as vital entry points for building trust in AI technologies. Finally, observability relates to the visibility of AI's benefits within the community. If early adopters experience significant improvements in yields or reduced input costs through AI, others in their networks are more likely to follow suit (Rogers, 2003).

The framework adopted in this study therefore integrates AI applications, socio-cultural factors, and adoption outcomes to explain technology diffusion. It emphasizes that adoption in Edo State is not solely determined by technological efficiency but is mediated by cultural practices, gender relations, social trust, and communication dynamics within farming communities. Farmers' reliance on peer influence, local leaders, and extension officers means that successful diffusion of AI will require embedding the technology within existing socio-cultural and institutional structures.

In this regard, extension agents serve as change agents, bridging the gap between technological innovation and community acceptance, while also tailoring AI applications to local contexts (Munyua, 2019). Building on this perspective, integrating DOI theory with the socio-cultural dynamics of Edo State further demonstrates that the adoption of AI in agriculture is not merely a technological act but a process deeply rooted in cultural and social contexts. Such an integrated view offers a more holistic understanding of technology diffusion, underscoring the importance of aligning AI innovations with farmers' values, traditional practices, and lived experiences to ensure sustainable adoption.

2.3 Concept of Artificial Intelligence (AI)

Artificial Intelligence (AI) is a multidisciplinary field within computer science that focuses on designing and developing systems capable of executing tasks that normally require human intelligence (Russell & Norvig, 2021). These tasks encompass a wide

array of cognitive functions, including reasoning, learning from experience, problem-solving, perception of the environment, natural language understanding, and informed decision-making (Nilsson, 2010). The overarching goal of AI is to replicate or enhance human cognitive capabilities, allowing machines to process complex data, detect patterns, predict outcomes, and make autonomous decisions with minimal human oversight (Shen, Li and Xu, 2020).

From a functional perspective, AI systems leverage advanced algorithms, mathematical models, and computational methods to simulate human reasoning and learning processes. Machine learning, a subset of AI, enables systems to adapt and improve performance based on accumulated data, while deep learning techniques mimic neural networks in the human brain to handle complex tasks such as image and speech recognition (Liakos *et al.*, 2018). Additionally, AI integrates perception capabilities through sensors, cameras, and natural language processing to interpret environmental cues and interact effectively with human operators or other systems.

Conceptually, AI is not limited to technical execution but also represents a framework for transforming raw data into actionable knowledge, thereby supporting informed decision-making in dynamic and uncertain environments (Shen *et al.*, 2020). This ability to analyze large datasets and provide predictive insights underpins its transformative potential across sectors such as healthcare, finance, transportation, and agriculture. In agriculture specifically, AI technologies facilitate precision farming, crop monitoring, pest and disease detection, and resource optimization, demonstrating how AI can extend

human decision-making and increase efficiency in complex operational contexts (Liakos *et al.*, 2018; Russell and Norvig, 2021).

Artificial Intelligence systems are commonly classified into two main categories: narrow (weak) AI and general (strong) AI. Narrow AI refers to systems that are designed and trained to perform specific tasks within a limited domain. Examples include speech and voice recognition, image classification, predictive modeling, and recommendation systems (Russell and Norvig, 2021). Narrow AI does not possess general reasoning capabilities; it excels only within the tasks for which it is programmed. This type of AI is the most prevalent in real-world applications and has been widely adopted across sectors such as agriculture, healthcare, finance, and manufacturing. In agriculture, for instance, narrow AI is used for precision farming applications including crop disease detection, soil nutrient analysis, yield prediction, and automated irrigation control (Liakos *et al.*, 2018).

In contrast, general AI refers to theoretical systems that possess the ability to perform any intellectual task that a human can accomplish. Such systems would demonstrate flexible problem-solving, reasoning, and learning across multiple domains without being restricted to a specific function (Nilsson, 2010). General AI remains largely a conceptual and experimental construct, as no system currently possesses the broad cognitive versatility of the human mind. While research continues toward its development, practical applications remain confined to narrow AI systems that address defined, domain-specific problems.

In the agricultural domain, Artificial Intelligence (AI) encompasses a diverse set of technologies that collectively support data-driven, precise, and efficient farming practices. These technologies include machine learning algorithms, which enable predictive analytics and pattern recognition; computer vision systems, which facilitate automated monitoring of crops for growth, nutrient status, and disease detection; robotics, which can perform repetitive or labor-intensive tasks such as planting, weeding, and harvesting; and decision-support systems, which integrate multiple data sources to guide optimal farm management decisions (Liakos *et al.*, 2018). By leveraging these tools, farmers are able to implement precision agriculture, characterized by site-specific interventions that optimize the use of inputs such as water, fertilizers, and pesticides. Applications include automated irrigation systems that adjust water delivery based on real-time soil moisture data, crop disease detection using image recognition and predictive modeling, yield forecasting based on historical and environmental data, soil quality assessment through sensor integration, and supply chain optimization that minimizes post-harvest losses.

Furthermore, when AI is integrated with sensor networks, drones, and satellite imagery, it enables real-time monitoring and spatial analysis of farm conditions, allowing farmers to make timely and informed decisions. This integration enhances operational efficiency, reduces waste of critical resources, and contributes to increased agricultural productivity and sustainability. Studies have shown that such AI-driven approaches can substantially improve yield outcomes, lower input costs, and reduce environmental impacts,

demonstrating the transformative potential of AI technologies in modern agriculture (Liakos *et al.*, 2018; Shen *et al.*, 2020).

Conceptually, Artificial Intelligence (AI) extends beyond being a mere technological tool; it represents a systematic framework for converting vast and complex datasets into actionable insights that can inform decision-making (Russell and Norvig, 2021). Through the use of advanced algorithms, machine learning techniques, and computational models, AI systems can detect patterns, uncover relationships, and generate predictive outcomes from large volumes of structured and unstructured data. This capability enables farmers, agribusiness managers, and policymakers to make informed decisions in environments characterized by uncertainty and dynamic changes, such as fluctuating weather patterns, pest outbreaks, and market variability (Liakos *et al.*, 2018).

Moreover, the adoption and effective utilization of AI technologies are determined not only by their technical sophistication but also by a range of socio-economic, institutional, and infrastructural factors. Access to digital infrastructure, the level of technological literacy among users, availability of extension support, financial capacity, and policy frameworks all influence the extent to which AI can deliver meaningful benefits (Shen *et al.*, 2020). In agricultural systems, this means that while AI has the potential to optimize resource use, improve productivity, and enhance sustainability, its real-world impact is contingent upon contextual enablers such as farmer education, institutional support, and robust infrastructure. Consequently, integrating AI into agriculture requires not only technological deployment but also strategic interventions that address social, economic,

and institutional barriers, ensuring that the benefits of AI adoption are both effective and equitable.

Artificial Intelligence (AI) embodies both a scientific field of study and a suite of practical technologies designed to replicate, simulate, or enhance human cognitive functions. As a scientific discipline, AI investigates methods for enabling machines to perceive, reason, learn, and make decisions, while as a practical toolset, it provides actionable solutions that can be applied across multiple sectors, including healthcare, finance, manufacturing, and agriculture (Russell and Norvig, 2021; Nilsson, 2010). In the agricultural domain, the relevance of AI is particularly pronounced due to its capacity to optimize production processes, improve resource-use efficiency, and facilitate data-driven decision-making. By leveraging AI technologies such as machine learning, computer vision, robotics, and decision-support systems, farmers and agribusinesses can monitor crop health, predict yields, manage inputs, and plan supply chains with greater precision and effectiveness (Liakos *et al.*, 2018; Shen *et al.*, 2020). Ultimately, the integration of AI into agricultural systems contributes to sustainable development by increasing productivity, reducing waste, minimizing environmental impact, and supporting informed management decisions that are responsive to dynamic environmental and market conditions. Thus, AI is both an enabler of technological innovation and a strategic framework for achieving efficient, sustainable, and resilient agricultural practices.

2.4 Farmers' and Extension Agents' Adoption of Artificial Intelligence (AI)

The adoption of Artificial Intelligence (AI) in agriculture is a multifaceted process that is significantly shaped by the interactions between farmers, as the primary end-users, and extension agents, who function as intermediaries facilitating technology transfer, training, and knowledge dissemination. Farmers' decisions to adopt AI technologies are influenced by multiple factors, including their level of awareness and understanding of the technology, perceived economic and productivity benefits, access to financial and physical resources, and socio-economic characteristics such as education, farm size, and market connectivity (Ekpe *et al.*, 2022; Eze and Nwachukwu, 2021). Well-informed and resource-endowed farmers are more likely to recognize the potential of AI tools for precision agriculture, automated irrigation, yield prediction, and pest management, thereby increasing adoption likelihood (Liakos *et al.*, 2018).

Extension agents play a critical role in bridging the gap between technological innovation and practical application on farms. They provide technical guidance, demonstrate the use of AI-driven tools, and offer problem-solving support, which reduces uncertainty and builds farmers' confidence in adopting new technologies (Olowu and Kariuki, 2022; Yusuf and Ibrahim, 2023). By interpreting complex AI outputs, advising on decision-making based on data insights, and linking farmers with digital infrastructure and agritech providers, extension agents enhance the effectiveness and sustainability of AI adoption.

Moreover, the synergy between farmers' characteristics and extension support determines the overall adoption outcomes. Studies have shown that regular interaction with extension services, combined with access to digital infrastructure, training programs, and institutional support, significantly improves adoption rates, particularly among smallholder farmers who may otherwise face barriers such as low technological literacy and limited capital (Shen *et al.*, 2020; Okeke, 2023). Therefore, fostering effective collaboration between farmers and extension agents, alongside supportive policies and infrastructure, is essential for scaling AI technologies in agriculture and achieving equitable productivity gains.

2.5 Farmers' Adoption of AI

Farmers are more likely to adopt AI-based technologies when they perceive clear and tangible benefits, including enhanced productivity, reduced operational costs, and more efficient resource management. Key AI applications in agriculture such as precision agriculture tools, automated irrigation systems, crop disease detection algorithms, and yield prediction models enable farmers to make data-driven decisions that optimize input use, reduce wastage, and improve overall farm profitability (Liakos *et al.*, 2018). In the Nigerian context, empirical studies indicate that adoption tends to be higher among farmers who possess larger landholdings, greater access to financial resources, higher levels of formal education, and reliable connectivity to digital infrastructure (Ekpe *et al.*, 2022; Eze and Nwachukwu, 2021). These factors enhance the farmers' ability to understand, implement, and maintain AI technologies effectively.

Conversely, smallholder and resource-constrained farmers often encounter significant barriers that limit adoption. These challenges include high initial investment costs, insufficient technological literacy, limited exposure to training programs, and inadequate access to digital networks or infrastructure (Akinyemi and Adewale, 2017; Okeke, 2023). Such constraints create adoption gaps, as farmers who cannot overcome these barriers may be unable to realize the full potential of AI-driven interventions. Consequently, targeted strategies—such as subsidized technology provision, capacity-building initiatives, and improved digital connectivity—are essential to support wider and more equitable adoption of AI technologies in Nigerian agriculture.

2.6 Extension Agents' Role in AI Adoption

Extension agents serve as pivotal intermediaries in the adoption of Artificial Intelligence (AI) in agriculture, functioning as a bridge between technological innovations and farmers' practical needs. They provide training, technical support, and demonstration services that equip farmers with the knowledge and skills required to implement AI-driven solutions effectively. By interpreting complex outputs from AI tools, advising on the integration of data-driven practices, and facilitating interactions between farmers and technology providers, extension agents reduce the perceived complexity and uncertainty associated with new technologies (Yusuf and Ibrahim, 2023).

The effectiveness of extension services in promoting AI adoption is closely tied to the agents' digital literacy, understanding of AI applications, and access to relevant tools and

datasets (Olowu and Kariuki, 2022). Agents with sufficient technical competence are better positioned to translate AI insights into actionable guidance for farmers, thereby increasing adoption rates. Empirical evidence suggests that farmers who maintain regular contact with extension agents are more likely to adopt modern agricultural technologies, including AI-based interventions, because these interactions enhance awareness, build confidence, and improve understanding of potential benefits (Eze and Nwachukwu, 2021). Furthermore, extension agents play a critical role in fostering institutional and social support networks that encourage technology uptake. By connecting farmers to financial institutions, agritech firms, and pilot programs, they help overcome structural barriers such as limited access to capital or digital infrastructure. In the Nigerian context, strengthening the capacity of extension services through targeted training, provision of digital tools, and improved institutional support is therefore essential to scale AI adoption among both smallholder and commercial farmers (Shen *et al.*, 2020).

2.7 Combined Influence on Adoption

The overall adoption of Artificial Intelligence (AI) technologies in agriculture is strongly influenced by the interplay between farmers' socio-economic characteristics and the quality of extension support. While the technical feasibility of AI solutions is a necessary condition, it alone is insufficient to drive widespread adoption. Factors such as farmers' education, digital literacy, access to capital, farm size, and connectivity to digital infrastructure significantly affect their ability and willingness to adopt AI-driven tools

(Ekpe *et al.*, 2022; Eze and Nwachukwu, 2021). Simultaneously, the presence of proactive extension services that provide training, technical guidance, and demonstrations enhances farmers' confidence, reduces uncertainty, and facilitates practical implementation of AI technologies (Shen *et al.*, 2020; Yusuf and Ibrahim, 2023).

Integrated strategies that combine capacity-building for farmers, provision of accessible AI tools, supportive institutional policies, and robust extension networks are therefore critical to scaling adoption. Such approaches not only increase adoption rates but also promote equitable distribution of benefits across different categories of farmers, ensuring that smallholders are not left behind in the digital transformation of agriculture (Okeke, 2023). By addressing both technical and socio-institutional dimensions, policymakers and development stakeholders can create an enabling environment in which AI technologies contribute effectively to productivity gains, sustainable resource use, and resilience in agricultural systems.

In the Nigerian agricultural context, the adoption of Artificial Intelligence (AI) remains highly uneven, with commercial and well-connected farmers generally reaping the greatest benefits, while smallholder and resource-constrained farmers are often left behind (Ekpe *et al.*, 2022; Okeke, 2023). This disparity is largely driven by differences in access to digital infrastructure, financial resources, education, and technical support, as well as variations in exposure to extension services. Smallholders frequently face multiple adoption barriers, including high initial investment costs, limited technological

literacy, insufficient training opportunities, and inadequate outreach from extension services (Akinyemi and Adewale, 2017; Olowu and Kariuki, 2022).

To promote more equitable adoption, it is critical to implement integrated strategies that combine subsidized or affordable AI tools, capacity-building programs for farmers, strengthened extension networks, and supportive institutional policies (Shen *et al.*, 2020; Yusuf and Ibrahim, 2023). Such interventions can help bridge the digital divide, enhance farmers' confidence and competence in using AI technologies, and ultimately scale adoption across diverse farming communities. By addressing both technical and socio-economic constraints, stakeholders can maximize the potential of AI to improve productivity, optimize resource use, and advance sustainable agricultural development in Nigeria.

2.8 Empirical Review

Several empirical studies have investigated the adoption of artificial intelligence (AI) and related digital technologies in agriculture across Nigeria, including Edo State. These works provide insights into how socio-cultural, economic, and institutional factors shape adoption outcomes. Studies show that while Nigeria's agricultural sector is gradually embracing AI and digital technologies, adoption remains uneven due to infrastructural and socio-cultural barriers. For example, Aker (2011) highlighted how digital tools such as mobile phones improved agricultural extension and information flow across sub-Saharan Africa, laying the foundation for AI-driven innovations. More recent works, such

as Ogunlela and Mukhtar (2020), observed that precision farming and AI-based decision-support tools are being introduced in southern Nigeria, including Edo State, but uptake is constrained by limited awareness, cultural beliefs, and affordability.

In Edo State specifically, empirical work has indicated a growing awareness of digital tools in farming. Omoregbee and Banmeke (2014) studied farmers' use of ICTs in agricultural information dissemination in Edo State and found that while mobile phones and radio were widely adopted, advanced technologies such as AI-driven platforms were still novel and less utilized. This suggests that adoption is influenced not only by availability but also by cultural perceptions of relevance. Similarly, Okunlola *et al.* (2019) reported that socio-cultural factors such as communal decision-making, gender roles, and trust in extension agents significantly shaped the willingness of farmers in Edo State to embrace new agricultural innovations.

Empirical findings also stress that farmers' socio-cultural backgrounds determine their openness to AI. Munyua (2019) emphasized that indigenous knowledge systems may either facilitate or hinder technology integration, depending on how AI is contextualized. In Edo State, for instance, farming cooperatives and peer influence were found to play a critical role in technology adoption (Omoregbee *et al.*, 2016). When early adopters in a community embraced digital innovations, others were more likely to follow. However, resistance emerged when AI applications conflicted with traditional practices, reflecting Rogers' (2003) diffusion theory.

Another key empirical observation is the mediating role of extension agents. Ajayi and Gunn (2021) demonstrated that extension workers in Edo and neighboring states served as cultural translators of digital technologies, framing AI recommendations in ways that were locally acceptable. This mediation reduced skepticism and improved adoption rates, confirming that socio-cultural adaptation is as critical as technological availability.

The outcomes of adoption have been mixed. Empirical studies report improved productivity, cost reduction, and enhanced decision-making among farmers who successfully integrated AI tools (Sharma *et al.*, 2020; Kamilaris and Prenafeta-Boldú, 2018). However, in Edo State, empirical findings reveal slow and uneven adoption, particularly among smallholder farmers, due to socio-cultural resistance, low literacy levels, and mistrust of machine-generated advice (Omoregbee and Banmeke, 2014; Okunlola *et al.*, 2019).

In their conference case study, Akinyemi and Adewale (2017) examined the feasibility and adoption potential of precision agriculture within a maize plantation in Nigeria, highlighting the relevance of site-specific management strategies for improving productivity. The researchers employed remote sensing technologies and image classification techniques to assess spatial and temporal variability within the farm, revealing significant differences in soil fertility, moisture content, and crop performance across fields. These variations, they argued, could be effectively addressed through targeted interventions such as variable-rate seeding, site-specific fertilization, and tailored irrigation, demonstrating the technical applicability of precision agriculture under

Nigerian conditions. Despite the promising outcomes, the study identified several critical constraints limiting widespread adoption. High initial investment costs for precision equipment, a shortage of locally trained personnel capable of operating and maintaining the technology, and weak extension service support emerged as major barriers. Akinyemi and Adewale further noted that without adequate institutional and infrastructural support, smallholder and medium-scale farmers may be unable to realize the potential benefits of precision agriculture, underscoring the need for policy incentives, training programs, and locally adapted technologies to enhance adoption rates in the Nigerian context.

Ekpe Shen *et al.* (2022) conducted a cross-sectional survey to investigate the level of knowledge and the adoption patterns of precision agriculture among smallholder oil-palm farmers in Essien Udim communities in Nigeria. The study aimed to assess not only the farmers' awareness of digital and site-specific farming practices but also the socio-economic and institutional factors influencing their adoption decisions. Using structured questionnaires and face-to-face interviews, the researchers collected data on farm size, farmer education, access to extension services, perceived profitability, and infrastructural support. Their analysis revealed that overall awareness of precision agriculture technologies was low, indicating a significant knowledge gap among smallholder farmers. Adoption tended to be concentrated among larger farms and those with better social and market connectivity, suggesting that resource endowment and network access play crucial roles in technology uptake. The study further identified several key determinants of adoption: farmers' education level, regular contact with extension agents, and the

perceived economic benefits of precision agriculture practices. Conversely, high costs of inputs and equipment, limited availability of demonstration sites, and inadequate rural infrastructure were highlighted as major constraints. Ekpe *et al.* (2022), concluded that for wider diffusion of precision agriculture among smallholders, policy interventions should focus on improving farmer education, strengthening extension services, providing accessible demonstration programs, and subsidizing the cost of precision tools to make them more affordable and accessible.

Eze and Nwachukwu (2021) conducted a multi-state empirical survey in Nigeria to investigate the determinants of modern agricultural technology adoption among smallholder farmers. The study aimed to identify the socio-economic, infrastructural, and institutional factors that either facilitate or constrain farmers' uptake of digital and innovative farming practices. Data were collected through structured questionnaires administered to a representative sample of farmers across different agro-ecological zones. Using regression analysis, the authors examined the influence of key variables, including access to digital infrastructure, farmer education levels, frequency of extension service contact, and perceived profitability of technology adoption. The results indicated that access to digital tools and infrastructure, higher education levels among farmers, and regular engagement with extension agents significantly increased the likelihood of adopting modern agricultural technologies. Conversely, high input costs, insecure land tenure, and limited access to credit were found to hinder adoption. Eze and Nwachukwu emphasized that achieving broader adoption of modern technologies requires integrated

interventions that simultaneously enhance rural connectivity, strengthen extension services, and address economic and institutional barriers. The study concluded that policy measures focusing on these areas could significantly improve the diffusion of digital agricultural innovations in Nigeria, particularly among smallholder farmers.

Okeke (2023) conducted a comprehensive study on the determinants of data-driven agricultural technology (DDAT) adoption among smallholder farmers in Nigeria, with the aim of understanding both individual and institutional factors that influence uptake. The research employed a mixed-methods approach, combining analysis of a nationally representative household dataset with in-depth interviews of farmers, extension agents, and agritech stakeholders. Logistic regression was used to quantify the direct effects of variables such as digital infrastructure availability, farmers' digital literacy, and access to training programs, while mediation analysis examined how collaboration among stakeholders influenced adoption outcomes. The findings indicated that access to reliable digital infrastructure and higher levels of digital literacy among farmers directly increased the likelihood of adopting DDATs. Furthermore, collaborative interactions involving NGOs, extension services, and private agritech firms acted as a significant mediator, enhancing adoption by facilitating knowledge transfer, technical support, and access to digital tools. The study concluded that scaling data-driven agricultural technologies in Nigeria requires integrated interventions that simultaneously improve digital infrastructure, build farmers' technical skills, and foster multi-stakeholder collaboration. Okeke highlighted the importance of coordinated policies and programs

that bridge technological, human, and institutional gaps to ensure equitable and sustainable adoption of digital farming innovations across smallholder communities.

Olowu and Kariuki (2022) conducted a comparative empirical study to examine the adoption of cloud-based precision agriculture technologies among farmers in Nigeria and Kenya. The study aimed to identify the factors that facilitate or constrain the uptake of these advanced digital tools in different African contexts. Data were collected through structured surveys administered to commercial and smallholder farmers, supplemented by expert interviews with agritech startups, extension agents, and policymakers. The findings revealed that adoption levels in Nigeria lagged behind those in Kenya, primarily due to weaker rural connectivity, limited availability of service providers, and underdeveloped digital infrastructure. Despite these challenges, interest in cloud-based precision agriculture was rising among commercial farmers, particularly those with higher resource endowments and access to markets. The study also highlighted key barriers, including the high cost of technologies, lack of interoperability between platforms, and limited availability of local data services. Conversely, enablers of adoption included private-sector pilot projects, donor-supported initiatives, and targeted extension services. Based on these insights, Olowu and Kariuki recommended the development of stronger digital ecosystems, strategic partnerships among stakeholders, and investment in infrastructure to facilitate broader adoption of cloud-based precision agriculture in Nigeria. The study underscored that adoption is not solely a matter of technology

availability but also depends on institutional support, market access, and policy interventions tailored to local contexts.

Yusuf and Ibrahim (2023) conducted an econometric analysis to investigate the relationship between digital agricultural innovations, land acquisition strategies, and food security outcomes among Nigerian farmers. Using farm-level panel data, the study assessed how the adoption of digital tools such as data-driven crop management systems, mobile-based advisory platforms, and precision-farming technologies affects crop productivity and household food security indicators. The results indicated that the use of digital agricultural technologies significantly enhanced crop yields and contributed to improved food security. However, the benefits were not uniformly distributed across all farms. Larger farms and those with greater access to markets realized proportionally higher gains, highlighting disparities in the capacity to leverage technological innovations. The study further identified that structural and institutional factors, such as access to finance, market linkages, and land tenure security, influenced the effectiveness of technology adoption. Yusuf and Ibrahim concluded that policy interventions aimed at complementing digital innovation particularly through improved market access, financial inclusion, and equitable land distribution are critical to ensuring that the benefits of digital agricultural tools are broadly shared among smallholder and resource-constrained farmers. The study emphasizes the need for integrated strategies that combine technology adoption with supportive institutional and economic frameworks to achieve sustainable food security in Nigeria.

CHAPTER THREE

3.0 METHODOLOGY

3.1 Study Area

The study was conducted in Edo State. Edo State is in the Southern region of Nigeria bordered by Delta, Ondo, Kogi and Anambra States. Edo State lies within the geographical coordinates of Latitudes 5044'N and 7034'N and Longitude 5 004'E and 06043'E (Alakpa *et al.*, 2021). The State covers an area of 17,802km² and has a population of 3,233,366 (Koyenikan and Omoregie, 2022). The State is made up of urban and rural communities and is divided into three agro-ecological zones: Edo North, Edo Central, and Edo South. Agriculture remains a significant part of the state's economy, with a diverse range of crops and an active network of smallholder farmers and extension agents (Orewa and Izekor, 2012). This diversity makes Edo State a suitable context for examining the socio-cultural effects of AI in agriculture. The study covered the three agro-ecological zones.

3.2 Sample and Sampling Technique

The target population consisted of farmers and extension agents in Edo State. It included 436 registered farmers in Edo State (Edo State ADP Zonal Head Quarters, 2017) and 146

extension staffs in Edo State as distributed as 48 in Edo North, 48 in Edo Central and 50 in Edo South (Edo state ADP Zonal Head Quarters, 2025). The sampling procedure was a stratified sampling method with proportional allocation across registered farmers and agricultural extension agents. Each stratum was assigned a specific sampling percentage based on its population size to ensure fair representation. For the farmers, 30% of the population (436 registered farmers) was sampled resulting in a sample size of 131 farmers, which was proportionally distributed among the three agricultural zones. Agricultural extension agents was sampled at 56.85% of their population (146 extension agents), yielding 82 participants; 27, 27 and 28 respondents from Edo North, Edo Central and Edo South respectively.

3.3 Data Collection Method

Primary data was collected for this study, using the questionnaire and oral interview schedule for the farmers and extension agents. The questionnaire was structured according to the specific objectives of the study. Data were analyzed using Descriptive (Frequency Count, Mean and Percentages) and Inferential (ANOVA, Pearson Correlation) Statistics.

3.4 Measurement of Variables

The study considered two set of variables: Dependent Variable which is the perceived socio-cultural impacts or effects of Artificial Intelligence (AI) on Agriculture and the Independent Variables (socio-economic characteristics) such as age, gender, education

level, household size, years of experience and so on was collected through the questionnaire. Categorical variables were coded appropriately for analysis.

- **Age:** was measured in years.
- **Sex:** was measured as male =1, female = 2.
- **Marital status:** was measured as single = 1, married = 2, divorced = 3, separated = 4 and widowed = 5.
- **Religion:** was measured as Christian = 1, Muslim = 2, Traditional = 3
- **Location:** was measured as urban =1, rural = 2
- **Household size:** was measured according to the number of persons living together in a household
- **Level of Education:** was measured as no formal education = 1, primary education =2, secondary = 3, tertiary = 4
- **Source of Finance:** was measured as personal savings =1, relatives/friends = 2, bank loan = 3, cooperative = 4
- **Source of Labour:** was measured as family labour = 1, hired labour = 2, both = 3
- **Years of Experience:** was measured as 1- 5 years = 1, 6 – 11 years = 2, 11 – 15 years = 3, above 15 years = 4

3.5 Analytical Technique

This section described the specific analytical techniques that was used to analyze the collected data.

Objective 1: Socio-economic characteristics of the respondents was analyzed using descriptive statistics such as frequency counts, mean and percentages. Socio – economic characteristics such as age of the respondents was measured in years; sex measured as either male or female; marital status was measured as single = 1, married = 2, divorced = 3, separated = 4, widowed = 5; household size was measured according to the numbers of persons living together in a household; educational qualification was measured as non-formal education = 1, primary education = 2, secondary = 3, tertiary =4. Years of experience was measured as 1-5 =1; 6-10 = 2; 11-15= 3; above 15 = 4.

Objective 2: Awareness of Artificial Intelligence (AI) was analyzed using frequency and percentages. A two – point type scale was used: Yes = 2, No = 1

Objective 3: Current adoption levels of Artificial Intelligence (AI) by respondents was analyzed using mean derived from a 4 – point Likert type scale frequency and percentages. A two – point type scale was used; Yes = 2, No = 1.

Objective 4: Perceived socio-cultural effects of Artificial Intelligence (AI) technologies by respondents was analyzed using a 4 – point Likert type scale of strongly agree =1, agree =3, disagree =2, strongly disagree =1.

Objective 5: Difference in the perceived sociocultural effects of AI (Ag Tech) on agriculture among respondents was analyzed using Analysis of Variance (ANOVA).

3.6 Test of Hypothesis

Hypothesis 1: There is no significant relationship between the socio-economic characteristics of respondents and their level of awareness of AI.

Pearson correlation was used to find the relationship between the socio-economic characteristics of respondents and their level of awareness of AI.

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n \sum x^2 - (\sum x)^2][n \sum y^2 - (\sum y)^2]}}$$

r = Correlation coefficient

n = Number of observations

x = Variable X

y = Variable Y

CHAPTER FOUR

4.0 PRESENTATION OF RESULTS AND DISCUSSION OF FINDINGS

4.1 Socio-economic characteristics

4.1.1 Gender

Table 2 shows that the gender representation in the study was generally divided between male and female; males constituted 62.40% of the farmers and 61.67% of the extension agents, while females constituted 37.60% of the farmers and 38.33% of the extension agents. Findings from the study revealed that a majority of the farmers (62.4%) and extension agents (61.7%) were male. This result indicates that agricultural production and extension service delivery in the study area are still dominated by men. This gender imbalance reflects existing sociocultural norms and land tenure systems that often limit women's access to productive resources and decision-making authority in agriculture. It is imperative to note that of the 82 extension agents given questionnaires, only 60 completed questionnaires was retrieved and used for the study. Also, out of the 131 farmers given questionnaires to fill, only 125 successfully filled and returned their questionnaires used in the study.

According to the World Bank (2022), men generally have greater control over land and production assets in sub-Saharan Africa, which enhances their visibility and participation in agricultural programs. Doss and Morris (2021) further noted that despite such disparities, empowering women in agricultural technology adoption significantly improves household productivity and innovation diffusion. Therefore, while male

dominance reflects the current structural pattern, gender inclusiveness remains crucial for enhancing technology dissemination.

4.1.2 Age range (years)

The results showed that most farmers (57.6%) and extension agents (63.3%) were between 31 and 50 years of age. This age group represents individuals in their productive years, typically characterized by energy, openness to innovation, and readiness to experiment with new technologies. Younger and middle-aged farmers are generally more receptive to technological innovations compared to older farmers, who may prefer traditional methods due to risk aversion (Mendola, 2018). Similarly, extension agents within this age range are likely to be more technologically literate and adaptable to digital tools, thereby enhancing their capacity to transfer AI-based agricultural knowledge to farmers. This finding aligns with da Silveira *et al.* (2023) young people are easily adaptable to technology.

4.1.3 Marital Status

The result in Table 4.1 shows that a significant majority of both farmers (87.2%) and extension agents (81.7%) were married, indicating a socially and economically stable respondent population. Marital status appears to play a positive role in influencing technology adoption behavior, as married individuals are often more motivated to enhance productivity and household welfare through innovative practices. This aligns with Wossen *et al.* (2019) and Akinbode *et al.* (2023), who found that marriage fosters

long-term planning and collaborative decision-making, which support technology uptake. Conversely, the relatively small proportion of single respondents may suggest limited engagement in full-time agricultural activities, consistent with Gil *et al.* (2023), who observed that marital status interacts with age and household structure to shape adoption patterns. Overall, the predominance of married respondents creates a favorable social environment for collective learning, risk management, and sustained adoption of AI technologies in agriculture

4.1.4 Household Size range

The household size distribution shows that majority (72.0%) of farmers had between 1–4 household members, only a few (28.0%) had between 5–8 members. This implies that the majority of the farmers operated within small to medium-sized households. Smaller households may have limited access to unpaid family labour, which can affect the scale and intensity of farming operations. However, it also suggests lower dependency ratios and potentially greater efficiency in resource allocation. According to Wossen *et al.* (2019), smaller household sizes may limit the labour available for labour-intensive agricultural activities but can enhance per capita income and decision-making efficiency. Similarly, Akinbode *et al.* (2023) observed that small household sizes are becoming common among educated and semi-urban farmers who increasingly depend on hired labour rather than large family labour pools. Hence, the predominance of small households in this study reflects a shift toward semi-commercialized and knowledge-based agriculture among respondents.

4.1.5 Farm Size - ha (range)

The distribution of farm size shows that 72.0% of farmers cultivated less than or equal to 1.0 hectare, 27.2% managed between 1.1–2.0 hectares, and only 0.8% cultivated above 2.0 hectares. This clearly indicates that most respondents were smallholder farmers, consistent with Nigeria’s national agricultural structure, where smallholders dominate the sector. The relatively small farm sizes suggest that adoption of advanced AI-based technologies may be constrained by limited capital and economies of scale. However, smaller farms can also benefit from technologies designed for precision and efficient resource management. Da Silveira *et al.* (2023) reported that smaller landholders tend to adopt digital and precision tools selectively, particularly those that provide immediate returns or reduce labour intensity. Similarly, Gil *et al.* (2023) found that smallholders are more likely to use mobile-based AI applications rather than large-scale automation systems. Therefore, the prevalence of small farm holdings highlights the need to adapt AI innovations to small-scale contexts, focusing on affordability and accessibility.

4.1.6 Location

The results reveal that 46.4% of farmers resided in urban areas, 33.6% in rural areas, and 20.0% in semi-urban locations. In contrast, among extension agents, 43.3% were located in rural areas, 38.3% in semi-urban areas, and only 18.3% in urban centers. This distribution indicates that while most farmers are concentrated in urban and peri-urban areas, possibly reflecting proximity to markets and digital infrastructure, extension agents

are more evenly distributed across rural and semi-urban locations, where they serve as links between farmers and innovation systems. Carrer *et al.* (2022) noted that proximity to urban centers often facilitates faster exposure to digital and AI-based technologies due to better connectivity and access to extension services. Conversely, rural dwellers may face infrastructural and informational barriers. The relatively high representation of extension agents in rural settings suggests strong potential for technology diffusion, provided connectivity and training gaps are addressed.

4.1.7 Educational qualification

The results in Table 4.1 show that 89.6% of farmers and 95.0% of extension agents possessed tertiary education, while only 4.8% of farmers and 5.0% of extension agents had secondary education as their highest qualification. This indicates that the majority of respondents were highly educated, particularly among extension agents, who are formally trained professionals in agricultural development. The high level of education among both groups suggests that respondents are likely to be receptive to technological innovations, including Artificial Intelligence (AI) applications in agriculture. Education enhances the ability to process new information, interpret technical content, and apply scientific knowledge to farming practices. As such, educated farmers are generally more capable of understanding the operational requirements and benefits of AI technologies. According to Akinbode *et al.* (2023), education significantly influences digital technology adoption, as literate farmers are better positioned to navigate information and communication technologies (ICTs) and mobile-based platforms. Similarly, Carrer *et al.*

(2022) observed that education plays a pivotal role in the acceptance of precision agriculture and data-driven tools, given that users with tertiary education are more confident in managing complex technological systems.

The predominance of tertiary-educated respondents also reflects the evolving profile of Nigerian agriculture, which is increasingly attracting younger, educated individuals who view farming as a business rather than a subsistence activity. This demographic transition enhances the potential for rapid AI technology diffusion, as education is positively correlated with innovation readiness and critical thinking.

4.1.8 Religion

In terms of religious affiliation, 86.4% of farmers and 81.7% of extension agents identified as Christians, while 12.8% of farmers and 16.7% of extension agents were Muslims. Only 0.8% of farmers and 1.7% of extension agents practiced traditional religion. The dominance of Christianity among respondents reflects the general religious composition of southern and central Nigeria, where Christianity is the majority faith. Religion, although not a direct determinant of technology adoption, can shape perceptions, moral judgments, and openness to innovation. Cultural and religious beliefs often influence how individuals interpret new technologies, particularly emerging ones like AI that may evoke moral or existential concerns. For instance, Ekperi, Ibrahim, and Adebayo (2024) found that some rural communities associate AI with supernatural or foreign control, reflecting religious apprehension about artificial intelligence.

4.1.9 Years of Experience

Regarding farming and professional experience, 54.4% of farmers and 61.7% of extension agents had 6–10 years of experience, while 20.8% of farmers and 15.0% of agents had 11–15 years. Only 4.0% of farmers and 5.0% of agents had more than 15 years of experience. This indicates that most respondents are relatively young professionals with moderate experience in their fields. The predominance of respondents within 6–10 years of experience implies that they are likely open to innovation and technology adoption, balancing practical experience with willingness to experiment. Akinbode *et al.* (2023) found that farmers within this experience range are more likely to adopt AI and digital tools compared to older, more conservative practitioners. Similarly, Da Silveira *et al.* (2023) highlighted that moderate experience enhances technology receptiveness, as individuals are confident in their farming knowledge yet adaptable to innovation. Hence, the respondents' experience profile suggests a favourable demographic for the diffusion and sustained adoption of AI technologies in agriculture.

4.1.10 Source of Labour

Regarding farming and professional experience, 54.4% of farmers and 61.7% of extension agents had 6–10 years of experience, while 20.8% of farmers and 15.0% of agents had 11–15 years. Only 4.0% of farmers and 5.0% of agents had more than 15 years of experience. This indicates that most respondents are relatively young

professionals with moderate experience in their fields. The predominance of respondents with 6–10 years of experience implies that they are likely open to innovation and technology adoption, balancing practical experience with willingness to experiment. Akinbode *et al.* (2023) found that farmers within this experience range are more likely to adopt AI and digital tools compared to older, more conservative practitioners. Similarly, Da Silveira *et al.* (2023) highlighted that moderate experience enhances technology receptiveness, as individuals are confident in their farming knowledge yet adaptable to innovation.

Analysis of labour sources indicates that 31.2% of farmers relied solely on family labour, 27.2% used hired labour, while 41.6% combined both. The predominance of mixed labour sources reflects a hybrid labour system, where farmers supplement family input with hired workers to meet seasonal or specialized labour demands. This pattern aligns with the findings of Wossen *et al.* (2019), who observed that labour flexibility is common among smallholders seeking to balance production costs and labour availability. Similarly, Songol *et al.* (2021) reported that the increasing adoption of labour-saving technologies such as automated irrigation and precision tools has reshaped traditional labour patterns in agriculture.

The result suggests that as farmers integrate AI technologies, reliance on both family and hired labour may shift toward more specialized tasks requiring technical training, particularly in operating smart equipment and digital systems.

4.1.11 Source of Finance

Findings show that 65.6% of farmers funded their agricultural activities through personal savings, 20.0% relied on relatives or friends, 8.8% obtained bank loans, and 5.6% accessed funds from cooperative societies. The dominance of personal savings indicates low institutional financial inclusion, which may limit capital investment in AI-based technologies that require upfront costs. According to Gil *et al.* (2023), financial constraints remain one of the biggest barriers to digital technology adoption among smallholders, as limited access to credit reduces the capacity to invest in innovative tools. Akinbode *et al.* (2023) also highlighted that self-financing farmers often adopt cheaper or incremental forms of digital technologies, while formal financing significantly enhances adoption of capital-intensive innovations like drones and automation systems. Thus, the reliance on personal savings underscores the need for targeted credit programs, cooperative funding, and microfinance schemes designed to support smallholder participation in digital transformation initiatives.

4.1.12 Cooperative membership

The results indicate that 81.6% of farmers and 83.3% of extension agents were not members of any agricultural association, while only 18.4% of farmers and 16.7% of agents reported membership in associations. The low level of organizational participation

suggests limited engagement in collective platforms that could facilitate knowledge sharing, capacity building, and collective access to resources. Da Silveira *et al.* (2023) observed that membership in farmers' associations enhances access to information, training, and input markets, thereby positively influencing technology adoption rates. Likewise, Carrer *et al.* (2022) emphasized that collective organization increases farmers' negotiation power and their inclusion in innovation networks. The current findings imply that limited association membership may hinder the rapid diffusion of AI technologies, as social learning and collective advocacy are key components of innovation adoption. Encouraging farmers' participation in cooperatives, digital learning groups, and producer associations could therefore strengthen social capital and facilitate more effective dissemination of AI-based agricultural innovations.

Table 4.1: Socio-Economic Characteristics

Characteristics	Options	Farmers		Extension agents	
		Freq.	%	Freq.	%
Gender	Female	47	37.60	23	38.33
	Male	78	62.40	37	61.67
	Total	125	100.00	60	100.00
Age range (years)	1	11	8.80	11	18.33
	2	48	38.40	23	38.33
	3	48	38.40	22	36.67
	4	18	14.40	4	6.67
	Total	125	100.00	60	100.00
Marital Status	Single	15	12.00	10	16.67
	Married	109	87.20	49	81.67
	Divorced	1	.80	1	1.67
	Total	125	100.00	60	100.00
Household Size range	1 - 4	90	72.00		
	5 - 8	35	28.00		
	Total	125	100.00		
Farm Size - ha (range)	<= 1.0	90	72.00		
	1.1 - 2.0	34	27.20		
	2.1+	1	.80		
	Total	125	100.00		
Location	Rural	42	33.60	26	43.33
	Urban	58	46.40	11	18.33
	Semi-urban (3)	25	20.00	23	38.33
	Total	125	100.00	60	100.00
Educational qualification	Secondary	6	4.80	3	5.00
	Tertiary	112	89.60	57	95.00
	Total	125	100.00	60	100.00

Religion	Christianity	108	86.40	49	81.67	
	Muslim	16	12.80	10	16.67	
	Traditional	1	.80	1	1.67	
	Total	125	100.00	60	100.00	
Years of Experience	1-5	26	20.80	11	18.33	
	6-10	68	54.40	37	61.67	
	11-15	26	20.80	9	15.00	
	>15	5	4.00	3	5.00	
	Total	125	100.00	60	100.00	
Source of Labour	Family	39	31.20			
	Hired	34	27.20			
	Both	52	41.60			
	Total	125	100.00			
Source of Finance	Personal savings	82	65.60			
	Relatives/ Friends	25	20.00			
	Bank loan	11	8.80			
	Cooperatives	7	5.60			
	Total	125	100.00			
	Membership of Association	No	102	81.60	50	83.33
		Yes	23	18.40	10	16.67
Total		125	100.00	60	100.00	

Source: Fieldwork, 2025.

4.2 Awareness of AI Technologies by Respondents

Table 4.2 presents the distribution of farmers' and extension agents' awareness of Artificial Intelligence (AI)-based agricultural technologies in the study area. The technologies covered include drones for crop monitoring, mobile applications for weather forecasting, soil sensors and moisture monitors, automated irrigation systems, AI-powered pest and disease detection, remote sensing, satellite imagery, precision farming tools, climate precision models, and blockchain technology for supply chain management. A four-point scale of awareness was employed, and responses were analyzed in percentages to identify which technologies were most recognized by respondents.

The results show that overall awareness of AI-based agricultural technologies among both farmers and extension agents was high, although levels varied across technologies. Farmers' awareness ranged from 29.6% (remote sensing) to 92.0% (mobile weather applications), while awareness among extension agents ranged from 36.7% (remote sensing) to 98.3% (mobile weather applications). This pattern suggests that accessible, low-cost, and mobile-based technologies recorded higher awareness compared to complex or capital-intensive ones such as blockchain and remote sensing.

4.2.1 Mobile Applications for Weather Forecasting

A very high proportion of both farmers (92.0%) and extension agents (98.3%) were aware of mobile applications for weather forecasting. This widespread awareness likely reflects the increased penetration of smartphones and mobile internet connectivity across

rural and peri-urban areas. The result supports Akinbode *et al.* (2023), who observed that mobile weather applications are among the most familiar and utilized digital tools in African agriculture because they provide timely and actionable information relevant to farm planning. The high awareness of these applications highlights their practicality and ease of use, suggesting that mobile-based AI tools are now mainstream entry points for technology diffusion in agriculture.

4.2.2 Climate Precision Models and Satellite Imagery

Similarly, awareness of climate precision models and satellite imagery was notably high among respondents. Approximately 89.6% of farmers and 93.3% of extension agents were aware of climate precision models, while 74.4% of farmers and 91.7% of extension agents recognized satellite imagery tools. These findings indicate strong awareness of technologies that support environmental monitoring and climate adaptation. This aligns with Gil *et al.* (2023), who reported raising awareness of climate-smart technologies in developing regions as a result of government and NGO interventions focused on climate resilience.

The relatively high awareness of satellite imagery among extension agents (91.7%) suggests that institutional exposure, training, and collaboration with meteorological agencies have enhanced understanding of geospatial applications. However, the slightly lower awareness among farmers (74.4%) points to limited technical familiarity with such systems. According to Wossen *et al.* (2019), farmers often depend on intermediaries,

particularly trained extension workers to interpret and translate satellite-based information into practical farming decisions. Thus, the high awareness of these technologies demonstrates growing recognition of AI tools for climate monitoring, though continued training and localization are required for effective utilization.

4.2.3 Drones and Precision Farming Tools

Moderate to high awareness levels were recorded for drones for crop monitoring (farmers 65.6%; agents 78.3%) and precision farming tools (farmers 62.4%; agents 83.3%). The higher awareness among extension agents can be attributed to professional training programs and exposure to innovation-driven projects within the agricultural sector. These results align with Carrer *et al.* (2022), who found that awareness of precision technologies correlates positively with access to extension demonstrations and institutional capacity-building activities.

The relatively high awareness among farmers indicates a growing familiarity with data-driven agricultural practices, although it remains lower than that of extension personnel. This underscores the latter's role as key intermediaries in disseminating knowledge and promoting the adoption of advanced technologies. As Meher (2023) observed, awareness and prior experience with digital tools are strong predictors of readiness to adopt precision agriculture. Overall, the findings suggest an ongoing transition toward digital and precision-oriented farming in the study area, supported by extension programs and demonstration activities.

4.2.4 Automated Irrigation Systems and Soil Sensors

Farmers and extension agents also demonstrated substantial awareness of automated irrigation systems (farmers 78.4%; agents 76.7%) and soil sensors and moisture monitors (farmers 60.8%; agents 76.7%). These technologies are directly linked to productivity optimization and efficient resource use two factors that enhance their relevance and visibility among farming communities.

The moderate-to-high awareness level of soil sensors and moisture monitors reflects a growing appreciation for technologies that improve water use and soil health management. This finding corroborates Akinbode *et al.* (2023), who reported that awareness of soil monitoring technologies is rising in Nigeria due to the need for adaptive responses to drought and soil degradation. Similarly, Carrer *et al.* (2022) emphasized that awareness tends to increase when farmers perceive direct benefits such as improved irrigation efficiency and yield outcomes. However, the gap between farmers and extension agents suggests that technical complexity and limited field demonstrations remain barriers to widespread understanding. Da Silveira, *et al.* (2023) further argued that without localized demonstrations and context-based training, smallholders often perceive such technologies as too abstract or irrelevant.

The growing awareness of automated irrigation systems also indicates recognition of technologies that address climate variability and water scarcity, both of which are pressing agricultural concerns. As these technologies directly improve productivity and

sustainability, their adoption potential is considerably high if training and infrastructural challenges are addressed.

4.2.5 AI-Powered Pest and Disease Detection

Awareness of AI-powered pest and disease detection tools was moderate among respondents, with 53.6% of farmers and 65.0% of extension agents acknowledging familiarity. This shows that while awareness is increasing, many respondents are still unfamiliar with specialized AI applications for pest management. The moderate awareness can be attributed to limited exposure to field demonstrations and pilot programs.

This finding is consistent with Songol *et al.* (2021), who reported similar patterns in East Africa, noting that awareness of digital pest detection tools is often constrained by inadequate technical training and field testing. The results suggest a need for targeted demonstration projects and capacity-building initiatives that showcase the practicality of AI-based pest and disease management tools. Increasing such exposure could significantly improve farmers' trust and confidence in digital diagnosis systems.

4.2.6 Remote Sensing

The lowest awareness levels were recorded for remote sensing technologies, with 29.6% of farmers and 36.7% of extension agents reporting familiarity. This low awareness highlights the technical complexity and infrastructural demands associated with remote sensing tools, which are often perceived as too advanced for smallholder operations.

Similarly, Gil *et al.* (2023), found that remote sensing technologies remain poorly understood among small-scale farmers because of their high cost and the need for expert interpretation.

The result points to a knowledge and accessibility gap that can be bridged through simplified user interfaces, localized examples, and visual training materials that demonstrate how remote sensing data can enhance crop monitoring and resource planning. Integrating remote sensing insights into mobile and extension platforms may also improve accessibility for end users.

4.2.7 Blockchain Technology for Supply Chain Management

Awareness of blockchain technology was relatively low among farmers (48.0%) and moderate among extension agents (68.3%). This finding reflects the emerging nature of blockchain applications in agriculture and limited exposure to its potential for improving transparency and traceability within agricultural supply chains.

Deji *et al.* (2023) observed that even among professionals, awareness of blockchain technology remains low in developing regions due to the scarcity of practical workshops, pilot initiatives, and field demonstrations. The moderate awareness among extension agents suggests some institutional exposure, but broader knowledge dissemination remains limited. Given blockchain's potential for ensuring product authenticity and enhancing market access, the inclusion of blockchain education in agricultural training curricula is necessary to boost understanding and eventual adoption.

Table 4.2: Awareness of AI Technologies

AI Technologies	Farmers		Extension agents	
	Freq	%	Freq	%
Drones for crop monitoring	82	65.60	47	78.33
Mobile apps for weather forecasting	115	92.00	59	98.33
Soil sensors and moisture monitors	76	60.80	46	76.67
automated irrigation systems	98	78.40	46	76.67
AI-powdered pest and disease detection	67	53.60	39	65.00
Remote sensing	37	29.60	22	36.67
Satellite imagery	93	74.40	55	91.67
Precision farming tools	78	62.40	50	83.33
Climate precision models	112	89.60	56	93.33
Block chain technology for supply chain management	60	48.00	41	68.33

Source: Fieldwork, 2025.

4.3 Source of Information or Learning About AI Technologies

Table 4.3 presents the distribution of information sources through which farmers and extension agents learned about Artificial Intelligence (AI) technologies in the study area. Understanding these information channels is crucial, as they determine not only how awareness is created but also how adoption decisions are formed and sustained over time. Respondents identified four major sources of information dissemination: fellow or other extension agents, media (radio, television, and internet), training/workshops, and other informal sources such as agricultural input dealers, non-governmental organizations (NGOs), and social media.

The results reveal that respondents relied more on interactive and experience-based information sources such as training and peer contact, than on mass media or formal communication channels. This reflects the continued importance of interpersonal and participatory communication in the spread of new agricultural innovations like AI technologies.

4.3.1 Fellow or Other Extension Agents

About 37.6% of farmers and 25.0% of extension agents reported that their primary source of information on AI technologies came from fellow or other extension agents. This highlights the significance of peer learning and professional interaction as key mechanisms for spreading technological knowledge. Farmers often view extension officers as trusted intermediaries and credible sources of information regarding modern

agricultural technologies. Likewise, extension agents themselves frequently exchange insights through professional networks, meetings, and collaborative projects—facilitating horizontal knowledge transfer within the agricultural extension system. According to Akinbode *et al.* (2023), interpersonal communication among extension personnel plays a pivotal role in reinforcing awareness and building confidence in emerging digital technologies. Similarly, Carrer *et al.* (2022) observed that informal exchanges among professional peers accelerate technology diffusion by fostering mutual learning and adaptive understanding of innovations. These findings underscore the importance of strengthening peer-to-peer learning channels such as field visits, farmer-to-farmer extension, mentoring programs, and discussion groups. Encouraging such social learning mechanisms can improve the circulation of information about AI technologies and support more rapid and confident adoption among both farmers and extension agents.

4.3.2 Media (Radio, Television, and Internet)

Only 20.8% of farmers and 13.3% of extension agents identified media outlets—such as radio, television, or internet platforms as their main source of information about AI technologies. Although mass media remains a powerful tool for disseminating agricultural information, its contribution in this study appears relatively limited. This may be attributed to a combination of factors, including low internet penetration in rural areas, limited programming content dedicated to AI innovations, and low digital literacy among farming populations.

Gil *et al.* (2023) noted that while mass media is effective for creating general awareness of agricultural innovations, its influence tends to diminish for complex technologies such as AI that require contextual understanding and hands-on exposure. Similarly, Songol *et al.* (2021), emphasized that media communication is most effective when combined with field-based demonstrations and interpersonal extension activities.

The relatively low proportion of respondents citing media as a key source of AI information suggests that agricultural communication through mass media is underutilized. There is a need to strengthen the role of radio, television, and mobile-based media in creating awareness about AI technologies particularly through community radio programs, short agricultural documentaries, and mobile text-based advisory systems. These media tools, when customized in local languages and integrated with on-ground extension activities, can reach broader audiences and effectively bridge information gaps.

4.3.3 Training and Workshops

Training and workshops emerged as the most significant sources of information, with 58.4% of farmers and 75.0% of extension agents identifying them as their main channels for learning about AI technologies. This finding demonstrates that structured capacity-building and experiential learning activities are the most effective avenues for disseminating information on AI innovations.

Training programs offer opportunities for direct interaction with experts, practical demonstrations of technologies, and active question-and-answer sessions, which together

enhance comprehension and retention. The high proportion of extension agents who cited training and workshops as their main information source suggests that they have greater institutional access to formal capacity-building opportunities. In contrast, farmers' lower percentage reflects less frequent exposure to organized training, which may limit their technical understanding.

Da-Silveira *et al.* (2023) found that participatory and hands-on workshops significantly increase farmers' understanding and acceptance of smart farming tools, especially when such sessions include demonstration farms and interactive learning components. Likewise, Akinbode *et al.* (2023) emphasized that formal training and workshops tend to have a greater impact on technology awareness and adoption than passive channels such as print or electronic media.

The results, therefore, highlight the importance of maintaining training and workshops as central pillars of agricultural extension strategies. Regularly organized, community-based capacity-building sessions using local language instruction, participatory demonstrations, and follow-up mentoring could further enhance awareness and translate knowledge into practical adoption of AI technologies.

4.3.4 Other Information Sources

A smaller proportion of respondents 8.9% of farmers and 3.4% of extension agents reported receiving information from "other sources," including NGOs, research institutions, agricultural input dealers, or social media platforms. Although relatively

small, this category signifies the growing diversification of agricultural information channels.

In recent years, NGOs and agritech startups have played an increasing role in promoting digital agricultural tools through pilot projects, e-extension platforms, and farmer training initiatives. Meher (2023) observed that social media platforms such as WhatsApp, Facebook, and YouTube are becoming popular tools for sharing agricultural knowledge among rural youth, particularly regarding AI and other emerging technologies. The presence of such alternative information channels in this study suggests the gradual digitalization of agricultural communication ecosystems, where both formal and informal actors contribute to innovation diffusion.

This finding suggests that while traditional extension channels remain vital, integrating digital and informal communication pathways, such as mobile-based applications, farmer groups, and private agribusiness networks, can complement public-sector efforts and expand the reach of AI awareness campaigns.

Table 4.3: Information sources of respondents on AI technologies

AI Technologies	Farmers		Extension agents	
	Freq	%	Freq	%
Fellow or other Extension agents	47	37.60	15	25.00
Fellow farmers	0	.00	0	.00
Media (radio, TV, internet)	26	20.80	8	13.33
Training/workshops	73	58.40	45	75.00
Others	11	8.87	2	3.39

Source: Fieldwork, 2025.

4.4 Adoption Level of AI Technologies

Table 4.4 presents the levels of adoption of various Artificial Intelligence (AI)-based agricultural technologies among farmers and extension agents in the study area. The technologies examined include drones for crop monitoring, mobile applications for weather forecasting, soil sensors and moisture monitors, automated irrigation systems, AI-powered pest and disease detection, remote sensing, satellite imagery, precision farming tools, climate precision models, and blockchain technology for supply chain management.

The results indicate that adoption levels are generally moderate to high for easily accessible and practical technologies such as mobile weather applications, satellite imagery, and climate precision models but low for complex or capital-intensive systems like remote sensing and blockchain technology.

4.4.1 Drones for Crop Monitoring

Adoption of drones for crop monitoring stood at 40.8% among farmers and 56.7% among extension agents. This moderate adoption rate reflects growing recognition of drones as valuable tools for crop health assessment, pest detection, and fertilizer optimization. However, high costs, limited access to drone operation training, and regulatory restrictions continue to hinder wider use among smallholder farmers.

According to Da Silveira *et al.* (2023), drone adoption among smallholders is strongly influenced by affordability, perceived usefulness, and technical capacity. The relatively

higher adoption among extension agents can be attributed to institutional access and involvement in demonstration projects, which increase exposure and familiarity with drone technologies. Subsidized access programs, cooperative drone ownership schemes, and targeted training for smallholders can enhance the adoption and operational sustainability of drone technologies in rural agriculture.

4.4.2 Mobile Applications for Weather Forecasting

Mobile applications for weather forecasting recorded the highest adoption levels—74.4% among farmers and 91.7% among extension agents. This finding reflects the widespread accessibility and practicality of mobile-based AI solutions. Farmers increasingly rely on these applications for critical decisions regarding planting, irrigation, and harvesting schedules.

Akinbode *et al.* (2023) found that mobile weather and advisory applications are among the most rapidly adopted AI tools in African agriculture due to their low cost and direct relevance to daily farm management. Similarly, Gil *et al.* (2023) emphasized that mobile-based AI platforms effectively bridge information gaps by providing localized, real-time data for smallholders. The popularity of mobile platforms provides an ideal entry point for scaling other AI technologies through integrated mobile advisory systems that can progressively introduce farmers to advanced digital tools.

4.4.3 Soil Sensors and Moisture Monitors

The adoption rate for soil sensors and moisture monitors was 40.8% among farmers and 55.0% among extension agents. This moderate level indicates growing appreciation for precision soil and water management, though widespread adoption remains limited by cost, technical know-how, and maintenance challenges. Carrer et al. (2022) reported that early adopters of soil monitoring tools often benefit from extension support and perceive visible yield gains, which motivate continued use. Da Silveira et al. (2023) further observed that hands-on demonstrations and locally adapted designs improve farmer acceptance of sensor technologies. Expanding localized demonstration plots and introducing simplified, cost-effective sensor models could enhance adoption and promote efficient resource management among smallholders.

4.4.4 Automated Irrigation Systems

Adoption of automated irrigation systems was 48.0% among farmers and 46.7% among extension agents, suggesting near parity in adoption between both groups. The results indicate increasing interest in water-efficient irrigation methods, especially where water scarcity poses production challenges.

Akinbode *et al.* (2023) observed that regions facing water shortages tend to adopt automated irrigation more quickly, particularly where public or private programs provide technical and financial support. However, infrastructural limitations, such as unreliable electricity and high setup costs, continue to restrict large-scale deployment. Integrating

solar-powered irrigation systems and community-based demonstration projects could expand adoption while promoting sustainability in water use.

4.4.5 AI-Powered Pest and Disease Detection

AI-based pest and disease detection systems recorded adoption rates of 34.4% among farmers and 40.0% among extension agents. These moderate figures reflect growing but cautious engagement with diagnostic AI technologies. Many farmers continue to depend on traditional pest identification and management methods, possibly due to limited trust or technical exposure to AI-based systems.

Songol *et al.* (2021) reported similar adoption levels in East Africa, attributing them to farmers' reliance on traditional practices and the absence of field-based demonstrations. Gil *et al.* (2023) added that building trust in AI-based models requires consistent accuracy and transparent validation mechanisms. Increased adoption could be achieved through participatory field demonstrations, mobile-based integration of pest advisory tools, and inclusion of AI pest detection in extension training curricula.

4.4.6 Remote Sensing

Remote sensing exhibited the lowest adoption rates—8.0% among farmers and 1.7% among extension agents. This extremely low adoption reflects technical, financial, and infrastructural constraints associated with the technology. Remote sensing requires specialized training, high-quality data processing infrastructure, and stable internet connectivity—all of which are scarce in smallholder farming contexts.

Carrer *et al.* (2022) and Gil *et al.* (2023) both identified high costs, data interpretation challenges, and lack of localized support as key barriers to remote sensing adoption.

Simplifying remote sensing interfaces and integrating satellite data into user-friendly mobile platforms could bridge the accessibility gap and improve adoption rates among both farmers and extension agents.

4.4.7 Satellite Imagery

Adoption of satellite imagery tools was relatively high 64.0% among farmers and 75.0% among extension agents. This reflects strong acceptance of satellite-based tools for crop monitoring, yield forecasting, and land-use assessment. Unlike remote sensing, satellite imagery is increasingly incorporated into mobile applications and national extension platforms, making it more user-friendly and practical.

Gil *et al.* (2023) reported similar trends in Nigeria and Kenya, attributing the growth to collaboration between meteorological and agricultural institutions providing real-time satellite advisory services. Enhancing the availability of open-access satellite imagery and developing localized interpretation support systems can further strengthen technology adoption and decision-making efficiency.

4.4.8 Precision Farming Tools

Adoption of precision farming tools stood at 45.6% among farmers and 53.3% among extension agents, reflecting a moderate-to-high adoption level. This trend demonstrates the gradual shift toward data-driven agriculture, where farmers use technology to

optimize inputs and reduce waste. Meher (2023) noted that education and perceived usefulness are strong predictors of precision farming adoption. Extension agents' higher adoption levels in this study can be attributed to their institutional exposure and training opportunities. To sustain and expand precision agriculture, programs should focus on affordability, digital literacy, and localized adaptation of precision tools to fit smallholder contexts.

4.4.9 Climate Precision Models

Climate precision models recorded adoption rates of 60.0% among farmers and 81.7% among extension agents, highlighting the increasing relevance of climate-smart agriculture in addressing weather-related risks. Farmers and extension agents rely on these tools for rainfall prediction, risk management, and planning decisions.

Both Gil *et al.* (2023) and DaSilveira *et al.* (2023) observed that exposure to climate advisory tools significantly improves adaptive capacity and technology acceptance, particularly when integrated with mobile delivery systems. Strengthening access to localized climate forecasting tools and offering training in their interpretation can enhance adaptive behavior and resilience among rural farmers.

4.4.10 Blockchain Technology for Supply Chain Management

Blockchain technology recorded relatively low adoption 35.2% among farmers and 41.7% among extension agents—indicating nascent but growing interest in digital

traceability and transparency tools. Limited understanding of blockchain concepts and a lack of enabling infrastructure constrain wider usage.

Deji *et al.* (2023) found similar results in Nigeria, noting that low awareness, technical complexity, and the absence of practical demonstrations hinder blockchain adoption in agricultural supply chains. Expanding pilot projects and integrating blockchain modules into agricultural value-chain training can promote awareness of its potential benefits, such as improved market trust and product traceability.

Table 4.4: AI Technologies adopted by respondents

AI Technologies	Farmers		Extension Agents	
	Freq	%	Freq	%
Drones for crop monitoring	51	40.80	34	56.67
Mobile apps for weather forecasting	93	74.40	55	91.67
Soil sensors and moisture monitors	51	40.80	33	55.00
automated irrigation systems	60	48.00	28	46.67
AI-powdered pest and disease detection	43	34.40	24	40.00
Remote sensing	10	8.00	1	1.67
Satellite imagery	80	64.00	45	75.00
Precision farming tools	57	45.60	32	53.33
Climate precision models	75	60.00	49	81.67
Block chain technology for supply chain management	44	35.20	25	41.67

Source: Fieldwork, 2025.

4.5 Perceived Socio-Cultural Effect of AI (Ag Tech)

Table 4.5 presents the mean responses and standard deviations of farmers and extension agents regarding their perceptions of the socio-cultural effects of Artificial Intelligence (AI) technologies in agriculture. The perception statements were measured on a four-point Likert scale where 1 = Strongly Disagree, 2 = Disagree, 3 = Agree, and 4 = Strongly Agree. A mean score of 2.50 and above was interpreted as agreement, while a mean score below 2.50 was interpreted as disagreement.

The results indicate that most respondents both farmers and extension agents held mixed perceptions toward AI technologies. While some items reflected a recognition of AI's potential role in modernizing agriculture, others revealed deep-seated cultural resistance and social apprehension about its compatibility with local values and traditions. This pattern suggests that attitudes toward AI in agriculture are not merely technical but are influenced by cultural, moral, and generational factors.

The mean scores of 3.46 and 3.35 shows that both farmers and extension agents generally agreed that AI technologies are against the culture of the people. This finding implies that AI innovations are perceived as culturally foreign and inconsistent with existing agricultural norms. The result supports the observation of Odetola and Eke (2022), who emphasized that cultural beliefs and traditional practices in rural African societies often conflict with the introduction of advanced technologies, resulting in hesitancy toward their adoption.

Similarly, both groups agreed that farmers may not be able to cope with AI technologies despite their level of education (farmers = 3.08; extension agents = 2.75). This reflects limited confidence in the ability of farmers to comprehend and operate complex AI-driven systems. The finding corresponds with Da Silveira *et al.* (2023), who noted that smallholder farmers often perceive AI as highly technical and intimidating, requiring extensive training and digital competence before practical application.

The groups also expressed the view that AI technologies are not socially acceptable (farmers = 2.96; extension agents = 3.07). This perception suggests that the integration of AI in agriculture has not yet achieved widespread social legitimacy and may be viewed with suspicion or skepticism. Gil *et al.* (2023) observed a similar trend among rural farmers in sub-Saharan Africa, where AI and digital technologies are sometimes perceived as threats to traditional livelihoods and human labor.

There was strong agreement that AI will disrupt the existing farming and cropping systems, as indicated by mean scores of 3.42 for farmers and 3.30 for extension agents. This reflects apprehension that the introduction of automation and data-based decision-making could alter established agricultural practices and crop cycles. The finding aligns with Wossen *et al.* (2019), who reported that agricultural modernization, while beneficial, can reduce farmers' autonomy and modify long-standing cultural routines associated with farming.

In a similar vein, both farmers (mean = 3.18) and extension agents (mean = 3.12) agreed that AI technologies will affect the norms and values of the people. This indicates a perceived threat that technological advancement could erode cultural identity, indigenous wisdom, and traditional cooperation structures within rural communities. Akinbode *et al.* (2023) asserted that for agricultural innovations to be effective, they must be introduced in a manner that is consistent with local norms and value systems.

Both farmers and extension agents also believed that AI will make the youth lazy, with mean scores of 3.01 and 2.85 among farmers and extension agents respectively. This view reflects concerns that technology-driven farming might discourage hard work and diminish the youths' physical participation in agricultural activities. This perception corroborates Songol *et al.* (2021), who reported that many rural farmers associate automation with idleness and see it as reducing the moral value of labor among younger generations.

Similarly, both groups agreed that many farmers would dislike agricultural products produced using AI technologies (farmers = 3.06; extension agents = 2.98). This suggests a likelihood of consumer resistance toward AI-assisted food production, possibly due to ethical, safety, or religious beliefs. According to Meher (2023), such skepticism is common in emerging economies where limited understanding of automation leads to doubts about the authenticity or purity of machine-assisted products.

The highest level of agreement among all items was recorded for the statement “AI is the devil’s plan to rule the world”, where farmers and extension agents recorded mean scores of 3.55 and 3.37 respectively. This finding highlights deep moral and spiritual reservations surrounding AI adoption in agriculture, possibly arising from misinformation or religious interpretations of modern technology. Ekperi et al. (2024) similarly found that many rural dwellers interpret AI and robotics as supernatural or “anti-human” interventions that could undermine divine or natural order, reinforcing fear-based opposition to their use.

In contrast, both groups disagreed that AI enhances knowledge and learning among farmers and extension agents (mean = 2.17 each). This indicates that respondents did not perceive AI as a tool for knowledge exchange or capacity development. The result reflects low awareness of AI’s educational benefits, such as mobile-based advisory services and data-driven training. Da Silveira *et al.* (2023) noted that insufficient digital literacy often limits farmers’ ability to recognize the informational value of AI systems.

Both farmers and extension agents further disagreed that AI adoption leads to changes in labour patterns and employment (farmers = 2.19; extension agents = 2.15). This may be because automation’s transformative effects on rural labour structures are not yet widely experienced within the study area. However, Gil *et al.* (2023) projected that as AI adoption deepens, there will likely be a shift from manual to analytical or managerial roles in agricultural labour distribution.

Likewise, both farmers (mean = 2.12) and extension agents (mean = 2.20) disagreed that AI technologies promote inclusiveness and participation in agriculture. Respondents appeared to view AI as favoring educated, resource-endowed, or technologically exposed individuals, leaving behind smallholder and less literate farmers. This supports Akinbode *et al.* (2023), who identified digital exclusion and socioeconomic inequality as significant barriers to the inclusive diffusion of AI in African agriculture.

In terms of cultural influence, farmers (mean = 2.46) and extension agents (mean = 2.62) moderately agreed that cultural beliefs and norms influence the acceptance of AI technologies. This suggests that religion, community leadership, and social customs significantly shape farmers' openness to digital innovations. The finding confirms Odetola and Eke (2022), who emphasized that local belief systems and traditional authorities act as powerful determinants of innovation legitimacy in rural areas.

Both groups disagreed that AI technologies improve the social status of adopters (farmers = 2.36; extension agents = 2.02). This indicates that adopting AI does not necessarily confer prestige or recognition within the community. In contrast, Wossen *et al.* (2019) reported that technology adopters in other regions are often perceived as innovators and leaders, suggesting that in this study area, social validation of innovation is still weak.

For the statement that AI reduces the role of indigenous knowledge in farming, farmers slightly agreed (mean = 2.68), whereas extension agents disagreed (mean = 2.37). This divergence shows that farmers are more sensitive to the perceived displacement of

traditional farming wisdom by digital solutions. Da Silveira et al. (2023) highlighted a similar concern that modern agricultural systems may inadvertently marginalize local experiential knowledge.

There was moderate agreement that AI causes generational gaps in farming communities (farmers = 2.90; extension agents = 2.70), indicating that younger farmers are more receptive to digital innovations than older ones. This generational divide was also documented by Songol *et al.* (2021), who found that enthusiasm for technology adoption tends to be higher among tech-savvy youths compared to elderly farmers who favor conventional methods.

Finally, both farmers (mean = 2.90) and extension agents (mean = 2.72) moderately agreed that AI adoption affects social relations within farming communities. This suggests that the introduction of digital technologies may gradually alter traditional patterns of communal labor, cooperation, and social interaction among farmers. As Ekperi et al. (2024) observed, automation and individual decision-support systems may weaken traditional social bonds, replacing cooperative networks with technology-driven independence.

Overall, the results reveal a duality of perception among respondents—while they acknowledge AI's potential to transform agriculture, they remain wary of its moral, cultural, and social implications. Farmers generally expressed stronger reservations than extension agents, reflecting their deeper connection to traditional practices and values.

The pattern also indicates that cultural beliefs, moral frameworks, and social norms play significant roles in shaping perceptions of AI.

These findings align with the Diffusion of Innovations Theory (Rogers, 2003), which posits that the perceived compatibility of a new technology with existing cultural and social systems significantly influences its acceptance. Thus, successful AI adoption in agriculture requires culturally sensitive strategies that build trust, dispel misconceptions, and demonstrate tangible local benefits.

Table 4.5: Perceptions of the socio-cultural effect of AI technologies

Effects	Farmers		Extension agents	
	Mean	SD	Mean	SD
AI (Ag Tech) is against the culture of the people	3.46	.5	3.35	.5
Farmers cannot cope with AI (Ag Tech) despite their level of education	3.08	.8	2.75	.7
AI (Ag Tech) is not socially acceptable	2.96	.6	3.07	.4
The AI (Ag Tech) will disrupt the farming and cropping system)	3.42	.6	3.30	.6
AI (Ag Tech) will affect the norms and values of our people	3.18	.6	3.12	.5
AI (Ag Tech) will make the youth to be lazy	3.01	.8	2.85	.8
Many farmers will dislike agricultural products from AI (Ag Tech)	3.06	.6	2.98	.7
AI (Ag Tech) is devils' plan to rule to world	3.55	.6	3.37	.8
AI enhances knowledge learning among farmers and extension farmers	2.17	.8	2.17	.7
AI adoption leads to changes in labour patterns and employment	2.19	.5	2.15	.5
AI technologies promote inclusiveness and participation in agriculture	2.12	.6	2.20	.7
Cultural beliefs and norms influence the acceptance of AI technologies	2.46	.6	2.62	.7
AI technologies improve the social status of the farmers or extension agents who adopt them	2.36	.7	2.02	.6
AI reduces the role of indigenous knowledge in farming	2.68	.7	2.37	.7
AI causes generational gaps in farming communities	2.90	.7	2.70	.8
AI adoption affects social relations within farming communities	2.90	.8	2.72	.7

*Agreed (mean > 2.50)

Source: Fieldwork, 2025

4.6 Test of Hypothesis

4.6.1 Relationship between the socio-economic characteristics and adoption of AI

Table 4.5 presents the regression estimates showing the relationship between selected socio-economic characteristics of respondents and their level of adoption of Artificial Intelligence (AI) technologies in agriculture. Separate regression models were estimated for farmers and extension agents. The model aimed to determine which socio-economic variables significantly influenced the likelihood of adopting AI technologies.

4.6.2 Farmers

For farmers, four variables sex, association membership, awareness of AI technologies, and location (marginally significant) were found to influence adoption positively.

Sex ($\beta = 0.162$; $t = 2.351$; $p = 0.020$) was statistically significant at the 5% level, implying that gender plays a significant role in AI adoption. The positive coefficient indicates that male farmers were more likely to adopt AI technologies than female farmers. This finding corroborates Carrer *et al.* (2022), who reported that male farmers often have greater access to technological resources and decision-making power in agricultural innovation adoption. Similarly, Akinbode *et al.* (2023) found that gender disparities in digital literacy and capital access contribute to male dominance in technology uptake.

Association membership ($\beta = 0.258$; $t = 4.007$; $p < 0.01$) also had a positive and significant effect, suggesting that farmers who belong to agricultural associations or

cooperatives are more likely to adopt AI technologies. This underscores the importance of social networks in promoting innovation diffusion. Cooperative groups often facilitate training, information sharing, and access to resources. Wossen *et al.* (2019) noted that membership in farmer associations enhances exposure to extension services, increases awareness, and encourages peer influence toward adopting new technologies.

Awareness of AI technologies ($\beta = 0.585$; $t = 8.513$; $p < 0.01$) emerged as the most significant determinant of adoption among farmers. The strong positive relationship indicates that increased awareness substantially enhances farmers' likelihood of adopting AI tools. This finding aligns with Gil *et al.* (2023), who emphasized that awareness and perceived usefulness are central predictors of digital technology adoption among smallholders. Da Silveira *et al.* (2023) similarly observed that awareness initiatives, when combined with demonstration-based learning, greatly influence adoption decisions in developing agricultural contexts.

Location ($\beta = 0.13$; $t = 1.915$; $p = 0.058$) was marginally significant, suggesting that geographical differences slightly influenced adoption. Farmers in more urban or peri-urban locations may have better access to ICT infrastructure and extension services, which facilitate exposure to AI-based agricultural technologies. This finding supports Odetola and Eke (2022), who highlighted that location and infrastructural disparities strongly affect digital adoption rates across rural communities.

Other variables, including age, education, years of experience, household size, and farm size, were statistically insignificant. The lack of significance for educational level ($p = 0.212$) implies that formal education alone does not necessarily translate into AI adoption; rather, targeted awareness and training are more influential. Similarly, years of farming experience did not significantly affect adoption, suggesting that experience may not necessarily equate to openness to new technologies.

4.6.3 Extension Agents

For extension agents, the regression model revealed that sex, age, location, and awareness of AI technologies were significant determinants of adoption.

Sex ($\beta = 0.274$; $t = 3.815$; $p < 0.01$) was positive and significant, indicating that male extension agents were more likely to adopt AI tools compared to their female counterparts. This supports Akinbode *et al.* (2023), who found gender-based disparities in access to ICT resources among extension professionals, often influenced by institutional biases and workload distribution.

Age ($\beta = 0.205$; $t = 2.369$; $p = 0.022$) was also significant and positively related to AI adoption, suggesting that older extension agents are more likely to adopt AI technologies. This may be due to their longer service duration, which provides greater exposure to institutional training and digital platforms. This finding contrast with some earlier studies (e.g., Songol *et al.*, 2021) that reported higher technology adoption among younger

agents but aligns with Da Silveira *et al.* (2023), who noted that professional experience can offset age-related digital gaps in formal institutional settings.

Location ($\beta = 0.603$; $t = 7.439$; $p < 0.01$) was the most significant determinant of adoption among extension agents. The positive coefficient implies that extension officers located in urban or semi-urban areas were far more likely to adopt AI technologies than those in rural areas. This may be attributed to the availability of digital infrastructure, better network connectivity, and more frequent exposure to innovation-driven programs in urban centers. Gil *et al.* (2023) similarly identified infrastructural access as a major determinant of digital technology uptake among agricultural service providers.

Awareness of AI technologies ($\beta = 0.329$; $t = 5.020$; $p < 0.01$) had a strong positive influence on adoption, confirming that awareness remains a central factor in determining the likelihood of using AI tools. This finding is consistent with the pattern observed among farmers and aligns with Rogers' (2003) Diffusion of Innovations Theory, which emphasizes awareness as the first and most critical stage in the adoption process.

Conversely, educational level and years of experience were not significant among extension agents ($p > 0.05$). This suggests that while education may enhance knowledge, it does not automatically translate to practical engagement with emerging technologies. Instead, hands-on training, workplace support, and infrastructural access appear to play stronger roles in influencing adoption behaviors.

Table 4.6: Regression estimates for the relationship between socio-economic variables and adoption of AI technologies

	Farmers			Extension agents		
	Standardized Coefficients	t-value	Prob. Level	Standardized Coefficients	t-value	Prob. Level
(Constant)		0.078	0.938		1.119	0.268
Sex	0.162*	2.351	0.020	0.274*	3.815	0.000
Age (years)	0.076	1.122	0.264	0.205*	2.369	0.022
Location	0.13	1.915	0.058	0.603*	7.439	0.000
Educational level	-0.086	1.254	0.212	0.045	0.646	0.521
Years of Experience	0.053	0.831	0.408	-0.163	1.651	0.105
Household Size	0.004	0.061	0.951			
Farm Size	-0.001	0.008	0.994			
Association Membership	0.258*	4.007	0.000			
Awareness of AI	0.585*	8.513	0.000	0.329*	5.02	0.000
Model Statistics						
F value	16.10; p<0.01			43.39; p<0.01		
Adjusted R square	0.523			0.808		

*Significant at 5%

Source: Fieldwork, 2025

CHAPTER FIVE

5.0 SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary

This study examined the socio-economic characteristics, awareness, information sources, adoption levels, and socio-cultural perceptions of Artificial Intelligence (AI) technologies among farmers and extension agents. The results showed that the majority of respondents were male, married, and within the productive age range of 31–50 years. Most farmers operated small farm holdings (≤ 1 hectare) and had small household sizes. Respondents were highly educated, predominantly with tertiary qualifications and possessed 6–10 years of professional experience, indicating a moderately experienced and literate population capable of engaging with digital technologies.

Awareness of AI technologies was generally high, particularly for mobile-based applications such as weather forecasting, satellite imagery, and climate precision models. However, awareness was relatively low for advanced tools like remote sensing and blockchain technology, largely due to technical complexity and limited exposure. Training and workshops emerged as the most important channels for AI-related information dissemination, followed by peer interactions among extension agents and farmers. This highlights the centrality of participatory and experiential learning in technology diffusion.

Adoption levels varied across technologies. Mobile weather applications, satellite imagery, and climate precision models recorded the highest adoption rates, while remote sensing and blockchain were the least adopted. These findings align with global trends where smallholders adopt low-cost, user-friendly, and practical innovations first. The regression results showed that for farmers, gender, association membership, location, and awareness of AI technologies significantly influenced adoption, while for extension agents, gender, age, location, and awareness were significant predictors. Awareness had the strongest effect in both groups, underscoring its pivotal role in facilitating adoption.

Perception analysis revealed a dual attitude toward AI technologies. While respondents acknowledged the potential benefits of AI for modernizing agriculture, many expressed cultural and moral reservations. Both farmers and extension agents agreed that AI might conflict with local traditions, affect social values, and alter traditional labour structures. Some even viewed AI as a “foreign” or spiritually threatening concept. However, these perceptions also reflected limited understanding and misinformation about AI’s actual role in agricultural transformation. The findings suggest that socio-cultural factors such as religion, moral values, and generational differences significantly shape acceptance and adoption of AI in agriculture.

5.2 Conclusion

The study concludes that while awareness and partial adoption of AI technologies are growing among farmers and extension agents, full-scale integration into agricultural

practice remains limited by socio-economic, cultural, and infrastructural barriers. The results affirm that awareness and access to information are critical determinants of adoption, consistent with Rogers' (2003) Diffusion of Innovations Theory. However, the persistence of cultural misconceptions and limited institutional support impedes the transition from awareness to practical use.

The predominance of educated, married, and moderately experienced respondents presents a favorable demographic base for scaling AI innovations. Yet, widespread adoption requires addressing financial, cultural, and infrastructural constraints. The findings emphasize that successful deployment of AI in agriculture must go beyond technical solutions, it should incorporate socio-cultural compatibility, trust-building, and human-centered design. Hence, policy interventions should not only focus on providing technology but also on strengthening awareness, building confidence, and aligning innovations with local realities.

5.3 Recommendations

Based on the study findings, the following recommendations are proposed:

1. **Enhance Awareness and Digital Literacy:** Government agencies, NGOs, and private agritech firms should intensify sensitization campaigns and capacity-building programs focused on AI technologies. Localized training in local languages, visual aids, and demonstration farms should be prioritized to improve comprehension and confidence among farmers.

2. **Promote Culturally Sensitive Innovation Strategies:** Extension programs should integrate cultural beliefs, moral values, and social dynamics into AI promotion strategies. Collaborating with community leaders and religious groups can help dispel myths and foster trust in technological innovations.
3. **Strengthen Extension and Peer Learning Systems:** Given the strong role of peer influence and workshops, investment in extension services should prioritize peer-to-peer learning models, digital extension platforms, and mentorship programs between experienced and novice farmers.
4. **Facilitate Access to Finance and Infrastructure:** Since personal savings remain the main source of funding for farmers, financial institutions should develop tailored credit schemes, grants, or cooperative funding models to support smallholders' investment in AI technologies. Government should also expand digital infrastructure such as rural broadband and electricity to create an enabling environment.
5. **Encourage Association Membership and Collective Action:** Strengthening farmers' cooperatives and professional associations can promote information exchange, collective bargaining, and collaborative adoption of AI tools. Social networks also serve as platforms for group-based training and advocacy.
6. **Integrate AI Training into Agricultural Curricula and Extension Programs:** Universities, agricultural colleges, and extension departments should include

modules on AI applications in agriculture, focusing on drone operation, data management, and digital decision-support systems.

7. **Support Research and Policy Development:** Policymakers should fund empirical research on AI's socio-economic and ethical implications in agriculture to inform culturally appropriate adoption frameworks. Establishing a national AI-in-Agriculture Policy could ensure coherent coordination among stakeholders.

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APPENDIX

RESEARCH QUESTIONNAIRE

**DEPARTMENT OF AGRICULTURAL ECONOMICS AND EXTENSION
SERVICES, FACULTY OF AGRICULTURE, UNIVERSITY OF BENIN,
BENIN CITY, NIGERIA**

Dear Respondent,

I am a final year student of the above Department. I am conducting a research on “**Socio-Cultural Effects of Artificial Intelligence (AI) in Agriculture by Farmers and Extension Agents in Edo State, Nigeria**”. Your true and sincere response will be highly appreciated. Your responses will be kept confidential and used for research purposes only.

Thank you for your time and cooperation.

Yours faithfully,

Emmanuel OLABAMERUN
Researcher.

INSTRUCTIONS: Please tick (√) and fill gap(s) where appropriate

Respondent Category: Farmer () Extension Agents ().

SECTION A: SOCIO -ECONOMIC CHARACTERISTICS

1. Gender: (a) Male () (b) Female ()
2. Age: _____ years
3. Marital status: (a) Single () (b) Married () (c) Divorced () (d) Separated ()
4. Location (Town/Village): _____
5. Local Government Area: _____
6. Educational Qualification: (a) No formal education () (b) Primary Education ()
(c) Secondary Education () (d) Tertiary Education ()
7. Religion: (a) Christianity () (b) Muslim () (c) Traditional ()
8. Occupation: (a) Farmer () (b) Extension Agent ()
9. Household size (for Farmers only): _____
10. Farm size (for farmers only) _____
11. Years of Farming/Extension Experience: 1- 5 years () (b) 6 – 11 years () (c) 11
– 15 years () (d) over 15 years ()
12. Source of Labour (for farmers only): (a) Family () (b) Hired () (c) Both (a&b) ()
13. Source of Finance (for farmers only: Personal savings () (b) Relatives/friends ()
(c) Bank loan () (d) Cooperative ()
14. Membership of Association? (a) Yes () (b) No ()
15. If yes, which Association? _____

SECTION B: AWARENESS OF AI TECHNOLOGIES BY FARMERS AND EXTENSION AGENTS

For Farmers Only:

16. Have you heard about Artificial Intelligence (AI) technologies used in agriculture?

(a) Yes () (b) No ().

17. If yes, which of the following AI technologies are you aware of? (Tick all that apply).

Items	Yes	No
Drones for crop monitoring		
Mobile apps for weather forecasting		
Soil sensors and moisture monitors		
Automated irrigation systems		
AI -powered pest and disease detection		
Remote sensing		
Satellite imagery		
Precision farming tools		
Climate prediction models		
Block chain technology for supply chain management		

18. How did you learn about these AI technologies? (a) Extension agents ()

(b) Fellow farmers () (c) Media (radio, TV, internet) () (d) Training/workshops ()

(e) others (please specify)_____

For Extension Agents:

19. Have you heard about Artificial Intelligence (AI) technologies used in agriculture?

Yes () (b) No ().

20. If yes, which of the following AI technologies are you aware of? (Tick all that apply).

Items	Yes	No
Drones for crop monitoring		
Mobile apps for weather forecasting		
Soil sensors and moisture monitors		
Automated irrigation systems		
AI -powered pest and disease detection		
Remote sensing		
Satellite imagery		
Precision farming tools		
Climate prediction models		
Block chain technology for supply chain management		

21. How did you learn about these AI technologies? (a) Extension agents ()

(b)Fellow farmers () (c)Media (radio, TV, internet) () (d)Training/workshops ()

(e) others (please specify)_____

SECTION C: ADOPTION LEVEL OF AI TECHNOLOGIES

Adoption Levels of AI Technologies (For farmers only):

22. Are you currently using any AI technologies in your farming activities? Yes () (b) No ().
23. If yes, which AI technologies do you currently use? (Tick all that apply).

Items	Yes	No
Drones for crop monitoring		
Mobile apps for weather forecasting		
Soil sensors and moisture monitors		
Automated irrigation systems		
AI -powered pest and disease detection		
Remote sensing		
Satellite imagery		
Precision farming tools		
Climate prediction models		
Block chain technology for supply chain management		

24. How often do you use AI technologies? (a) Daily () (b) Weekly() (c) Monthly() (d) Rarely ().

Adoption Levels of AI Technologies (For extension agents only):

25. Are you currently using any AI technologies in your extension activities? Yes ()

(b) No ().

26. If yes, which AI technologies do you currently use? (Tick all that apply).

Items	Yes	No
Drones for crop monitoring		
Mobile apps for weather forecasting		
Soil sensors and moisture monitors		
Automated irrigation systems		
AI -powered pest and disease detection		
Remote sensing		
Satellite imagery		
Precision farming tools		
Climate prediction models		
Block chain technology for supply chain management		

27. How often do you use AI technologies? (a) Daily () (b) Weekly () (c) Monthly ()

(d) Rarely ().

SECTION D: PERCEIVED SOCIO-CULTURAL EFFECT OF AI (AG TECH)

Perceived Socio-cultural Effect of AI (Ag Tech) (For farmers only):

Key: SA: Seriously Agree, A: Agree, D: Disagree, SD: Seriously Disagree.

S/N	ITEMS	SA	A	D	SD
1	AI (Ag Tech) is against the culture of the people,				
2	Farmers cannot cope with AI (Ag Tech) despite their level of education				
3	AI (Ag Tech) is not socially acceptable.				
4	The AI (Ag Tech) will disrupt the farming and cropping system.				
5	AI (Ag tech) will affect the norms and values of our people.				
6	AI (Ag Tech) will make the youths to be lazy.				
7	Many farmers will dislike agricultural products from AI (Ag Tech).				
8	AI (Ag Tech) is devils' plan to rule the world.				
9	AI enhances knowledge haring among farmers and extension agents.				
10	AI adoption leads to changes in labour patters and employment.				
11	AI technologies promote inclusiveness and participation in agriculture.				
12	Cultural beliefs and norms influence the acceptance of AI technologies.				
13	AI technologies improve the social status of the farmers or extension agents who adopt them.				
14	AI reduces the role of indigenous knowledge in farming.				
15	AI causes generational gaps in farming communities.				
16	AI adoption affects social relations within farming communities.				

Perceived Socio-cultural Effect of AI (Ag Tech) (For Extension Agents only):

S/N	ITEMS	SA	A	D	SD
1	AI (Ag Tech) is against the culture of the people.				
2	Farmers cannot cope with AI (Ag Tech) despite their level of education.				
3	AI (Ag Tech) is not socially acceptable.				
4	The AI (Ag Tech) will disrupt the farming and cropping system.				
5	AI (Ag tech) will affect the norms and values of our people.				
6	AI (Ag Tech) will make the youths to be lazy.				
7	Many farmers will dislike agricultural products from AI (Ag Tech).				
8	AI (Ag Tech) is devils' plan to rule the world.				
9	AI enhances knowledge haring among farmers and extension agents.				
10	AI adoption leads to changes in labour patters and employment.				
11	AI technologies promote inclusiveness and participation in agriculture.				
12	Cultural beliefs and norms influence the acceptance of AI technologies.				
13	AI technologies improve the social status of the farmers or extension agents who adopt them.				
14	AI reduces the role of indigenou knowledge in farming.				
15	AI causes generational gaps in farming communities.				
16	AI adoption affects social relations within farming communities.				