ADOPTION OF AI IN AGRICULTURAL ACTIVITIES: THE PROSPECTS AND CHALLENGES TO FARMERS AND TEACHERS IN AKWA IBOM STATE

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ABSTRACT

The study sought to examine the adoption of AI in agricultural activities, studying the prospects and challenges encountered by the farmers and teachers in Akwa Ibom State. To carry out the study, descriptive survey design was adopted. The study was carried out in Akwa Ibom State. The targeted population for the study comprised of all the farmers and teachers in Akwa Ibom state. A stratified random sampling technique was used to select a total of 60 teachers and 30 farmers, this gave a total of 90 respondents, which formed the sample size for this study. The instrument used for data collection was a structured questionnaire titled "AI and Agriculture Activities Questionnaire (AAAQ). Face and content validation of the instrument was carried out by an expert in test, measurement, and evaluation in order to ensure that the instrument has the accuracy, appropriateness, and completeness for the study under consideration. The reliability coefficient obtained was 0.83, and this was high enough to justify the use of the instrument. The researcher subjected the data generated for this study to appropriate statistical technique such descriptive statistics to answer research questions. This study concluded that AI helps in precision farming by analyzing soil data, weather, and crop conditions. This allows farmers to use the right amount of water, fertilizer, and pesticide only where needed. The study also recommended that governments, NGOs, and agricultural institutions should invest in training programs to improve digital literacy and teach farmers how to use AI-based systems, such as precision farming tools and crop monitoring platforms.

KEYWORDS: Artificial Intelligences, Agriculture Activities, Prospects and Challenges

INTRODUCTION

The agricultural sector stands on the brink of a technological revolution, driven by the integration of Artificial Intelligence (AI) into core farming operations. As the global population grows and climate change increasingly disrupts food production systems, the pressure on agriculture to become more efficient, resilient, and sustainable is immense. AI technologies—including machine learning, computer vision, robotics, and predictive analytics—are being adopted to tackle these challenges by optimizing input use, improving crop yields, and reducing waste. These technologies are enabling smart farming practices that align with precision agriculture principles, thereby reshaping traditional farming models and fostering innovation (Bhola, 2024; Parra-López, 2025).

The prospects of AI adoption in agriculture are substantial. Intelligent systems are now capable of performing a wide range of tasks such as crop health monitoring, soil condition analysis, pest detection, yield forecasting, and even autonomous machinery control. These innovations significantly enhance productivity and reduce human error, while minimizing environmental impact. For example, Abdelmoneim. (2025) document how AI integrated with IoT devices has revolutionized irrigation management, enabling real-time decisions that optimize water use and reduce resource waste. Similarly, AI is being used for disease prediction and management, contributing to improved plant and livestock health outcomes (Abdelmoneim, 2025; Jyoti, 2024).

Despite its promise, AI adoption in agriculture is uneven and faces multiple challenges. Barriers include high implementation costs, lack of digital infrastructure in rural areas, limited AI literacy among farmers, and concerns about data security. Smallholder farmers, particularly in developing countries, are often excluded from these advancements due to financial constraints and technological inaccessibility. Moreover, ethical concerns regarding automation-induced job losses and data ownership further complicate AI integration into agriculture. Parra-Lópe. (2025) emphasize the need for policy frameworks and institutional support to bridge these gaps and promote equitable AI diffusion across farming communities.

In response to these challenges, stakeholders—including governments, research institutions, and agritech firms—must work collaboratively to build an inclusive ecosystem that fosters sustainable AI adoption. Investment in training programs, infrastructure, and public-private partnerships is crucial for scaling AI solutions across diverse agricultural landscapes. Furthermore, localized AI models that address specific agro-climatic and socio-economic conditions can enhance relevance and effectiveness. As Fitas da Cruz (2024) points out, the transition to AI-driven agriculture must be strategically guided to ensure that it empowers rather than displaces farmers, ultimately contributing to a more resilient global food system.

Research Objective:

1. To examine the roles of Artificial Intelligence (AI) in agricultural activities as perceived by farmers and teachers in Akwa Ibom State.
2. To identify the challenges of adopting AI in agricultural activities as perceived by farmers and teachers in Akwa Ibom State.

Research Question:

1. What are the perceptions of farmers and teachers on the roles of Artificial Intelligence (AI) in agricultural activities in Akwa Ibom State?
2. What are the perceptions of farmers and teachers on the challenges of adopting AI in agricultural activities among farmers and teachers in Akwa Ibom State?

LITERATURE REVIEW

Concept of AI

Artificial intelligence (AI) is the simulation of human intelligence processes by machines, especially computer systems. Examples of AI applications include expert systems, natural language processing (NLP), and speech recognition and machine vision.Artificial intelligence (AI) is the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings. Artificial intelligence (AI) describes computer programs that are able to carry out sophisticatedoperations that were previously limited to human performance, such as problem-solving, thinking, and decision-making (Ufot, 2024).

Artificial intelligence (AI) is a set of technologies that enable computers to perform a variety of advanced functions, including the ability to see, understand and translate spoken and written language, analyze data, make recommendations, and more. Bassey and Owushi (2023) defined artificial intelligence as the collection of technologies that enable machines to sense, comprehend, act, and perform several functionsmatching those of humans.

Artificial intelligence is a field of science concerned with building computers and machines that can reason, learn, and act in such a way that would normally require human intelligence or that involves data whose scale exceeds what humans can analyze. Artificial intelligence refers to the research and programming of computers to carry outintelligence tasks that require human intervention (Udo-Okon and Akpan, 2024).

Artificial Intelligence (AI) refers to the technology that allows machines and computers to replicate human intelligence. It enables systems to perform tasks that require human-like decision-making, such as learning from data, identifying patterns, making informed choices and solving complex problems. AI improves continuously by utilizing methods like machine learning and deep learning.Furthermore, Ikechukwu (2024) mentioned that in contrast to the inherent intelligence of biological things, artificial intelligence (AI) is the broad definition of intelligence displayed bymachines, especially computer systems. By utilizing clever algorithms integrated into a dynamiccomputing environment, artificial intelligence mimics human thought processes. A branch ofcomputer science called artificial intelligence studies how computers learn, comprehend data,recognize characters in images, analyse pictures, and simulate how the eyes work

Concept of Agricultural Activities

Agricultural activities encompass the various processes we use to grow crops and raise livestock for food for human populations. Crops are also used for industrial processes, for example, palm oil is used in many products from frying oil to cosmetics, sugar cane waste is used for biofuel, and cotton is used for textiles. Livestock are used for meat, eggs, milk, as well as for leather and wool. Livestock are also used for labor. Nichepom, (2024),Agriculture refers to the practice of cultivating plants, raising animals, and producing food, fiber, and other agricultural products for human use. It is the process of harnessing and modifying the environment to grow crops, rear livestock, and manage natural resources to meet the needs of human populations.

Agricultural activities are defined as income-producing activities or uses that are characterized by the crop cultivation, not all of which are restricted to floral, fruits and veggies, vegetation, graze, and wood; and farming or raising livestock activities or uses that are connected to livestock farming, fish farming, and often game and fish propagation.Activities that are undertaken to convert a land area into farmland use really aren't considered to be part of a continuing operation.Mueller, Ulrich, Gerardo, Nicole, Aanen, Duur, Diana, Schultz & Ted, (2025),Agriculture is defined with varying scopes, in its broadest sense using natural resources to "produce commodities which maintain life, including food, fiber, forest products, horticultural crops, and their related services

Agricultural activities mean practices related to producing, breeding, or increasing agricultural products, rotating crops, managing land and operating agricultural facilities. Agricultural activities means the process of producing crops and/or raising or keeping livestock, which includes operation and maintenance of ponds, ditches, irrigation systems and the normal operation, maintenance and repair of existing structures or facilities, and practicing aquaculture.

Agricultural activities mean all activities pertaining directly to the production of crops or livestock, which could include, but is not limited to, cultivation, harvest, grazing, animal waste management, fertilization, operation and maintenance of structures, facilities or improved areas. Activities that bring an area into agricultural use are not considered agricultural activities.

The roles of AI in agricultural activities

Artificial Intelligence (AI) is playing an increasingly important role in modern agriculture. It helps farmers to make better decisions, increase productivity, and reduce waste. Below are the main areas where AI is being used:

- **Crop Monitoring and Disease Detection**

AI tools can detect diseases in crops early using images from drones or smartphones. Machine learning algorithms analyze these images and help farmers treat the crops before the disease spreads. For example, a study by Kamilaris and Prenafeta-Boldú (2020) shows how AI helps in identifying crop diseases through deep learning models.

- **Precision Farming**

AI helps in precision farming by analyzing soil data, weather, and crop conditions. This allows farmers to use the right amount of water, fertilizer, and pesticide only where needed. Liakos. (2021) explain how AI improves precision agriculture by using sensors and data analytics to make farming more accurate and cost-effective.

- **Yield Prediction**

AI models can predict how much crop will be harvested based on data such as weather, soil health, and past yields. This helps farmers plan better and reduce losses. According to a study by Chlingaryan. (2020), AI-based models are more accurate in predicting crop yields than traditional methods.

- **Weed and Pest Control**

AI systems, especially with computer vision, can identify weeds and pests so that pesticides can be applied only where needed. This saves money and protects the environment. Research by Sharma. (2022) shows that using AI-powered drones can improve pest control in large fields.

- **Automated Machinery and Robotics**

AI is used in self-driving tractors, harvesters, and drones. These machines can plant seeds, spray crops, and harvest automatically, saving time and labor costs. A review by Liu. (2021) discusses how AI-controlled robots are transforming farming practices.

- **Climate and Weather Forecasting**

AI models are used to predict weather patterns more accurately. This helps farmers plan the best time for planting and harvesting. A study by Zhang. (2023) explains how AI improves the accuracy of local weather forecasts used in farming.

- **Supply Chain Optimization**

AI helps track crops from the field to the market. It improves logistics, reduces food waste, and ensures better prices for farmers. According to Abbas. (2021), AI technologies help manage agricultural supply chains by predicting demand and improving storage and transport.

Strategic steps of using AI for planting

The use of Artificial Intelligence (AI) in agriculture has seen remarkable growth in recent years, significantly transforming the way planting is planned and executed. AI technologies offer new ways to optimize resources, increase crop yields, and reduce human error. For successful integration of AI into the planting process, several strategic steps must be followed. These steps ensure that AI systems are effectively implemented and provide meaningful, data-driven support to farmers.

- **Data Collection and Preprocessing**

The first strategic step in using AI for planting is the collection and preprocessing of relevant agricultural data. AI systems rely heavily on large volumes of data, such as soil composition, temperature, humidity, historical crop performance, and weather patterns. Technologies such as drones, satellite imagery, and soil sensors are commonly used to gather this information. Preprocessing involves cleaning the data—removing noise, correcting inconsistencies, and normalizing it—so it can be effectively used by AI models. According to Kamilaris and Prenafeta-Boldú (2020), high-quality data is essential for the success of AI applications in agriculture, as errors in data can significantly reduce the accuracy of predictions and recommendations.

- **Soil and Climate Analysis**

Once data is collected, AI can analyze soil properties and climatic conditions to determine the suitability of specific crops. AI models such as artificial neural networks can process large datasets to identify correlations between soil types, weather forecasts, and successful crop yields. This helps in making informed decisions about which crops to plant in a given region and season. For example, Khaki and Wang (2021) used deep learning models to predict crop yields based on soil and weather data, demonstrating that AI can outperform traditional statistical models in agricultural decision-making.

- **Seed Selection and Planting Optimization**

After identifying the most suitable crop, AI can assist in selecting the optimal seed varieties based on yield potential, disease resistance, and environmental compatibility. Machine learning algorithms recommend specific seed types for different zones within a farm, enabling what is known as "site-specific planting. “Additionally, AI enables precision planting by optimizing factors like seed depth, spacing, and planting time. Autonomous tractors and smart planters, guided by AI algorithms, are capable of placing seeds in exact locations and at consistent depths. This results in uniform germination and more efficient use of resources. Shamshiri. (2021) highlight how precision planting contributes to better crop establishment and resource efficiency.

- **Real-Time Monitoring and Adaptive Management**

Once planting is completed, AI systems continue to play a vital role through real-time monitoring. Sensors and computer vision tools monitor crop emergence, soil moisture, and early signs of stress or disease. AI models analyze this data and send alerts or suggest corrective measures, such as irrigation or nutrient application. This adaptive management approach allows farmers to make immediate adjustments in response to changing conditions, improving the resilience and health of crops. Liakos. (2020) emphasized that continuous monitoring supported by AI can significantly improve crop outcomes and reduce the need for reactive interventions

- **Predictive Analytics for Yield Forecasting**

The final strategic step is the use of AI for predictive analytics and yield forecasting. By analyzing patterns from previous growing seasons and incorporating current field data, AI models can forecast harvest outcomes with a high degree of accuracy. These forecasts help farmers plan for storage, marketing, and resource allocation. According to Khaki and Wang (2021), predictive models powered by AI not only help farmers anticipate crop yields but also assist in detecting potential risks early, such as droughts, pests, or diseases, allowing preventive actions to be taken in advance.

Strategic steps of using AI to eradicate unwanted plants

Weeds are among the most persistent and damaging threats to agricultural productivity. They compete with crops for vital resources such as water, nutrients, and sunlight, ultimately leading to reduced yields and increased farming costs. Traditional weed control methods often involve broad-spectrum herbicides and intensive labor, which may lead to environmental degradation, herbicide resistance, and rising production expenses. With the advancement of Artificial Intelligence (AI), a more sustainable and precise approach to weed eradication has become possible. This essay outlines the strategic steps involved in applying AI to identify and eliminate unwanted plants.

- **Data Acquisition and Annotation**

The first step in AI-driven weed eradication is acquiring high-quality visual data of farmlands. Drones, ground robots, and stationary cameras equipped with RGB, multispectral, or hyper spectral sensors are commonly used for capturing images of crop fields. These images are then annotated—manually or semi-automatically—to label weeds and crop regions. This annotated data is essential for training supervised learning models. According to Mardani. (2020), annotated datasets are foundational for teaching AI systems to differentiate between crops and weeds accurately, forming the basis for all further automation.

- **Model Training and Development**

Once annotated data is available, deep learning models—particularly Convolutional Neural Networks (CNNs) and object detection algorithms like YOLO (You Only Look Once)—are trained to identify weed patterns. These models learn from features like shape, size, and color to distinguish weeds from crops. Espejo-Garcia. (2020) emphasize that deep learning approaches have drastically improved weed detection performance, allowing models to achieve high levels of accuracy in varied agricultural environments.

- **Real-Time Weed Detection and Mapping**

Trained AI models are then integrated into drones or autonomous robots for real-time field operations. These systems scan the field, detect weed presence, and record geolocations to create weed infestation maps. This site-specific information enables targeted intervention rather than blanket spraying.

Dos Santos Ferreira. (2020) highlight how ConvNet-based detection systems improve the efficiency of weed monitoring by enabling real-time data processing and localized responses.

- **Precision Spraying and Mechanical Removal**

AI-guided machinery, such as smart sprayers and robotic weeders, use the detection maps to selectively apply herbicides or physically remove weeds. This targeted approach minimizes herbicide use and reduces environmental impact while preserving the health of crops. Lottes. (2021) showed that UAV-integrated AI systems significantly reduced chemical usage by enabling precision spraying based on AI-driven identification.

- **Feedback Systems and Continuous Learning**

After deployment, AI systems gather new field data during operations. This information is used to retrain and refine the models, improving their accuracy and adapting them to different seasons, crop types, or new weed species. Continuous learning enhances long-term performance. Jiang. (2021) point out that iterative learning allows AI systems to evolve and become more effective in handling complex and dynamic agricultural environments.

- **Integration with Farm Management Platforms**

The final strategic step is integrating AI weed control systems with broader digital agriculture platforms. These systems can be combined with irrigation, fertilization, and crop health monitoring tools to optimize overall farm productivity and sustainability. Wolfert. (2020) discuss the importance of integrating AI weed management with big data systems for smart farming, enhancing operational efficiency and resource optimization.

Strategic steps of using AI for harvest

- **Precision Farming: Enhancing Efficiency**

The precision agriculture process utilizes advanced technologies to optimize farming practices and enhance productivity. By integrating tools such as GPS, remote sensing, and data analytics, farmers can collect and analyze field-specific data to make informed decisions. This approach aims to address variability in crop and soil conditions, leading to more efficient resource use and improved yields. As global food demands rise and sustainability becomes increasingly important, precision agriculture offers a vital pathway for modern farming. The precision agriculture process consists of multiple stages cited Deepak, 2024).

- **Automated Monitoring and Predictive Analytics**

According to Haltan (2025), Predictive analytics is the use of statistics and modeling techniques to forecast future outcomes. Current and historical data patterns are examined and plotted to determine the likelihood that those patterns will repeat.

- **Smart Machinery and Robotics**

Asserted, Pratt (2011), A smart machine is a device embedded with machine-to-machine and/or cognitive computing technologies such as artificial intelligence (AI), machine learning (ML) or deep learning, all of which it uses to reason, solve problems, make decisions and even take action.

- **Crop Monitoring and Yield Prediction**

Cited ADMIN (2024), Crop yield prediction refers to the estimation of the amount of produce that a particular agricultural parcel or region is expected to yield during a given growing season. For several agricultural industry stakeholders, including farmers, legislators, researchers, and commodities merchants, and this projection is essential. Farmers can plan their irrigation schedules, apply fertilizer, control pests, and choose crops and planting densities with confidence when using an accurate yield estimate. Crop Yield Prediction are used by policymakers to plan agricultural policies, distribute funds, and handle issues related to food security. Crop Yield Prediction are also used by commodities traders to predict market movements and control price volatility-related risks.

- **Sustainable Agriculture Practices**

Sustainable agriculture can be defined as producing food and livestock over the long term with minimal negative effects on the environment. It is undertaken by a society with the goal of producing the greatest quantity of food over the longest time in order to feed a growing human population while keeping the environment intact according to Schap (2023).

- **Decision Support Systems**

A Decision Support System (DSS) is a collection of integrated software applications and hardware that form the backbone of an organization's decision making process. DSS is supported by different tools viz; DB query, Graphics, editor, OLAP, Statistical data analysis packages MS-Excel, Crystal, Analytical and think. These tools has wide variety of applicability in Industries rely on decision support tools, techniques, and models to assess and resolve today business questions. The decision support system is data-driven, as the entire process feeds off of the collection and availability of data to analyze.

Strategic steps of using AI for irrigation

- **Data Collection and Sensor Deployment**

The first step involves deploying IoT sensors in agricultural fields to collect real-time data on soil moisture, weather conditions, and crop health. This data serves as the foundation for AI models. For instance, Wankhede. (2021) emphasized the importance of soil sensors and weather data in developing intelligent irrigation systems. "Efficient irrigation scheduling heavily relies on real-time soil and climate data obtained through IoT-enabled sensors" (Wankhede, 2021).

- **Data Preprocessing and Integration**

Raw data collected from different sensors must be cleaned, normalized, and integrated. AI models require structured datasets for accurate predictions. According to Jain. (2020), data integration from heterogeneous sources is critical for optimizing AI performance in smart farming. "Data preprocessing is essential to harmonize inputs from multiple sensor types for consistent AI modeling" (Jain, 2020).

- **Model Training and Predictive Analysis**

Machine learning algorithms like Random Forest, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) are trained on historical and real-time data to predict optimal irrigation schedules. For example, Ramesh and Pandian (2021) demonstrated the use of ANN for predicting soil moisture levels with high accuracy. "AI models trained on historical and sensor data can predict future irrigation needs with over 90% accuracy" (Ramesh & Pandian, 2021).

- **Decision Support Systems (DSS)**

AI-powered DSS tools provide actionable recommendations to farmers or automatically control irrigation systems. Sarker. (2022) highlighted the role of AI in decision-making by integrating environmental, crop, and soil data. "The integration of AI in DSS enables real-time irrigation control and resource optimization" (Sarker, 2022).

- **Automation and Control Systems**

AI systems are often integrated with automated irrigation controllers such as drip or sprinkler systems. These systems can autonomously turn on/off based on AI-generated insights. According to Karthikeyan. (2020), automated irrigation saves water and improves crop yield. "Automated AI-based irrigation systems significantly reduce water consumption and labor costs" (Karthikeyan, 2020).

- **Feedback and Continuous Learning**

AI models require regular feedback from outcomes (e.g., crop yield, water usage) to improve future predictions. Reinforcement learning and adaptive algorithms are increasingly used in this step (Gandhi & Patel, 2023). "AI systems in irrigation must continuously learn from real-world outcomes to remain effective under changing climate conditions" (Gandhi & Patel, 2023).

- **Scalability and Integration with Farm Management Systems**

Finally, successful AI models must scale across diverse regions and integrate with broader farm management platforms for holistic agricultural planning. Singh. (2021) stressed the importance of interoperability. "Scalable AI systems that integrate with farm ERP platforms allow for a unified view of resources and productivity" (Singh, 2021).

Challenges of using AI for agricultural activities

- **High Cost of Implementation**

Implementing AI in agriculture requires significant financial investment in equipment such as drones, IoT sensors, high-resolution imaging tools, and data-processing infrastructure. Additionally, developing or purchasing AI software and hiring technical experts can be costly. These expenses are often beyond the reach of smallholder and resource-poor farmers, particularly in developing countries**.** “The cost of adopting AI technologies remains prohibitive for smallholder farmers, particularly in low-income countries” (Liakos, 2020).

- **Lack of Digital Infrastructure**

Many rural areas lack the basic digital infrastructure needed for AI to function effectively. Stable internet connections, cloud computing support, and reliable electricity are essential for real-time data transmission and remote decision-making, yet these are often unavailable in many agricultural regions. “The lack of rural connectivity and supporting digital infrastructure restricts the scalability of AI applications in agriculture” (Kamilaris & Prenafeta-Boldú, 2021).

- **Data Scarcity and Poor Data Quality**

AI models depend on vast, high-quality, labeled datasets for training and performance. However, in agriculture, especially in emerging economies, data on soil health, pest behavior, crop yields, and environmental variables is often incomplete, outdated, or inconsistently recorded. This limits the accuracy and reliability of AI-based predictions and decisions. "Incomplete and non-standardized agricultural datasets hinder the training of effective AI models" (Misra, 2022).

- **Low Technical Literacy among Farmers**

A significant proportion of farmers, especially older or rural populations, lack the education or digital skills needed to understand or interact with AI tools. This creates a gap between the technology and its intended users, resulting in underutilization or misuse. Effective AI use often requires basic understanding of devices, applications, and data interpretation. "Even when AI tools are available, their use is limited due to farmers' lack of technical skills and training" (Sharma, 2021).

- **Ethical and Data Privacy Concerns**

As AI in agriculture relies on extensive data collection (e.g., land usage, crop performance, satellite imagery), questions arise about data ownership, consent, and security. Farmers are often unaware of how their data is stored, shared, or monetized. Without clear policies and data governance frameworks, this can lead to exploitation or misuse. "AI in agriculture raises concerns about who owns the data and how it is used, necessitating stronger ethical frameworks" (Boursianis, 2022).

- **Environmental Variability and Poor Model Generalization**

AI models are usually trained using data from specific regions. When these models are applied to other locations with different climate conditions, crop types, or farming practices, their performance often declines. This lack of generalization limits the ability to scale AI solutions globally. "Model performance deteriorates when applied outside the original training environment, limiting AI's transferability" (Wang, 2023).

- **Integration Challenges with Traditional Farming Practices**

Many existing farms still use manual or semi-mechanized systems that are not compatible with AI technologies. Adapting these traditional systems to support digital platforms can be technically and logistically difficult. Additionally, farmers may resist change due to unfamiliarity or cultural attachment to existing practices. "Integrating AI into traditional farming frameworks remains a technical and organizational challenge" (Singh & Yadav, 2021).

Mitigating strategies to the challenges of using AI for agricultural activities

The integration of Artificial Intelligence (AI) in agriculture is reshaping the way farming is conducted, offering benefits such as optimized crop production, precision resource management, and early detection of pests and diseases. Despite its promising potential, AI adoption in agriculture faces several notable challenges. These include data scarcity, high implementation costs, limited technical know-how among farmers, and ethical or legal concerns. This essay explores these key challenges and outlines practical and research-backed strategies to mitigate them.

➢ Addressing Data Scarcity and Quality Issues

One of the most significant barriers to AI in agriculture is the lack of high-quality, annotated data. Most AI systems rely on large datasets to function accurately, but agricultural data is often inconsistent, unstructured, and unavailable in many regions.

To mitigate this, researchers and practitioners are turning to data augmentation and synthetic data generation techniques. Methods such as image rotation, noise injection, and the use of Generative Adversarial Networks (GANs) help in artificially expanding the datasets used for training AI models (Kamilaris & Prenafeta-Boldú, 2021). Additionally, open-source platforms and crowdsourcing initiatives like PlantVillage and FAO's WaPOR provide labeled datasets that support the development of robust models (Liakos, 2020). Furthermore, remote sensing technologies—such as drones and satellite imagery—can generate consistent and comprehensive datasets to fill existing gaps in on-ground data collection (Chlingaryan, 2020). Integrating such data with AI improves predictive capabilities and enhances decision-making in real time.

➢ Reducing High Implementation Costs

Another key challenge is the high cost of AI technology. Tools such as drones, smart sensors, and cloud-based data services are often too expensive for smallholder farmers, especially in low-income countries. To address this, several public–private partnerships (PPPs) have emerged, offering subsidies or co-financing models that reduce financial burdens on farmers. Governments, NGOs, and tech companies are collaborating to make AI-based technologies more accessible (Wolfert, 2020).In addition, the development of edge computing—where data processing occurs on local devices rather than expensive cloud platforms—combined with affordable IoT devices has significantly lowered operational costs (Mishra & Pradhan, 2021). Also, financial innovations like micro-financing and leasing models provide flexible payment structures that allow farmers to adopt AI incrementally (Wanjala, 2021).

➢ Overcoming Technical Complexity and Skills Gap

The technical sophistication of AI tools can be overwhelming for the average farmer, especially those in remote or underserved areas. Most farmers lack the training to operate AI-based systems effectively.To address this, many developers are creating farmer-centric AI tools with user-friendly interfaces and local language support. Applications that use voice inputs, for instance, reduce the need for digital literacy and make it easier for farmers to interact with AI systems (Reddy & Raju, 2021).Moreover, agricultural extension services play a crucial role by offering training sessions, workshops, and community-based demonstrations on how to use AI tools in farming (Ogunlela & Mukhtar, 2022). Another effective approach is AI-as-a-Service (AIaaS), where cloud-based analytics platforms provide decision-making tools without requiring users to understand the underlying algorithms (Misra, 2020).

➢ Navigating Ethical, Legal, and Privacy Concerns

The collection and processing of agricultural data also bring about ethical concerns, including data ownership, privacy, and the risk of surveillance. In many cases, the legal frameworks needed to regulate these concerns are either weak or non-existent. To counter this, there is an increasing push for the establishment of AI governance frameworks that clearly define data rights and responsibilities. These frameworks ensure transparency, accountability, and fairness in how data is collected and used (van der Burg & Bogaardt, 2021).One of the technological solutions gaining traction is federated learning, which allows AI models to be trained across multiple decentralized devices without transferring raw data, thereby preserving privacy (Yang, 2021). Additionally, ethical audits and AI impact assessments are being conducted to ensure that AI tools align with human rights and sustainable development goals (Floridi & Cowls, 2021).

METHODOLOGY

To carry out the study, descriptive survey design was adopted. The study was carried out in Akwa Ibom State. The targeted population for the study comprised of all the farmers and teachers in Akwa Ibom state. A stratified random sampling technique was used to select a total of 60 teachers and 30 farmers, this gave a total of 90 respondents, which formed the sample size for this study. The instrument used for data collection was a structured questionnaire titled "AI and Agriculture Activities Questionnaire (AAAQ). Face and content validation of the instrument was carried out by an expert in test, measurement, and evaluation in order to ensure that the instrument has the accuracy, appropriateness, and completeness for the study under consideration. The reliability coefficient obtained was 0.83, and this was high enough to justify the use of the instrument. The researcher subjected the data generated for this study to appropriate statistical technique such descriptive statistics to answer research questions.

Research Questions 1:

The research question sought to examine the roles of Artificial Intelligence (AI) in agricultural activities as perceived by farmers and teachers in Akwa Ibom State. To answer the research question percentage analysis was performed on the data, (see table 1).

Table 1:

Percentage Analysis of the Roles of Artificial Intelligence (AI) In Agricultural Activities as perceived by Farmers and Teachers in Akwa Ibom State.

Roles	Frequency	Percentage
Crop Monitoring and Disease Detection	26	28.89**
Precision Farming	22	24.44
Yield Prediction	17	18.89
Weed and Pest Control	11	12.22
Automated Machinery and Robotics	8	8.89
Climate and Weather Forecasting	6	6.67*
TOTAL	**90**	**100%**

** **The highest percentage frequency**
* **The least percentage frequency**
SOURCE: Field survey

The above Table 1 presents the percentage analysis of the roles of Artificial Intelligence (AI) in agricultural activities as perceived by farmers and teachers in Akwa Ibom State. From the result of the data analysis, it was observed that the highest percentage (28.89%) was recorded against "Crop Monitoring and Disease Detection", while the least percentage (6.67%) was recorded against "Climate and Weather Forecasting". This finding agrees with the opinion of Liakos (2021) who asserted that AI improves precision agriculture by using sensors and data analytics to make farming more accurate and cost-effective. According to him, AI helps in precision farming by analyzing soil data, weather, and crop conditions. This allows farmers to use the right amount of water, fertilizer, and pesticide only where needed. His opinion also aligns with that of Kamilaris and Prenafeta-Boldú (2020) who noted that AI tools can detect diseases in crops early using images from drones or smart phones. Machine learning algorithms analyze these images and help farmers treat the crops before the disease spreads.

Research Questions 2:

The research question sought to identify challenges of adopting AI in agricultural activities as perceived by farmers and teachers in Akwa Ibom State. To answer the research question percentage analysis was performed on the data, (see table 2).

Table 2:

Percentage Analysis of the challenges of adopting AI in agricultural activities as perceived by farmers and teachers in Akwa Ibom State

Challenges	Frequency	Percentage
High Cost of Implementation	20	22.22**
Lack of Digital Infrastructure	18	20.00
Data Scarcity and Poor Data Quality	16	17.78
Low Technical Literacy among Farmers	14	15.56
Ethical and Data Privacy Concerns	11	12.22
Environmental Variability and Poor Model Generalization	7	7.78*
TOTAL	**90**	**100%**

** **The highest percentage frequency**
* **The least percentage frequency**
SOURCE: Field survey

The above Table 2 presents the percentage analysis of the challenges of adopting AI in agricultural activities as perceived by farmers and teachers in Akwa Ibom State. From the result of the data analysis, it was observed that the highest percentage (22.22%) was recorded against "High Cost of Implementation", while the least percentage (7.78%) was recorded against "Environmental Variability and Poor Model Generalization". This finding agrees with the opinion of Kamilaris & Prenafeta-Boldú, (2021) who noted that many rural areas lack the basic digital infrastructure needed for AI to function effectively. Stable internet connections, cloud computing support, and reliable electricity are essential for real-time data transmission and remote decision-making, yet these are often unavailable in many agricultural regions, the lack of rural connectivity and supporting digital infrastructure restricts the scalability of AI applications in agriculture. His opinion also aligns with that of Liakos, (2020), who observed that developing or purchasing AI software and hiring technical experts can be costly. These expenses are often beyond the reach of smallholder and resource-poor farmers, particularly in developing countries, the cost of adopting AI technologies remains prohibitive for smallholder farmers, particularly in low-income countries.

CONCLUSION

The adoption of AI in agriculture holds immense potential to transform farming into a more efficient, data-driven, and sustainable enterprise. From precision farming to predictive analytics, AI offers solutions that can boost productivity and address food security. However, its integration is hampered by infrastructural gaps, high costs, and digital illiteracy. Smallholder farmers remain especially vulnerable to exclusion. For equitable adoption, targeted policies, inclusive technology design, and robust training programs are essential. Ethical concerns like job displacement and data privacy also require attention. With balanced implementation, AI can redefine agriculture for future resilience. Collaboration across sectors is key to unlocking this potential.

RECOMMENDATION

1. Governments, NGOs, and agricultural institutions should invest in training programs to improve digital literacy and teach farmers how to use AI-based systems, such as precision farming tools and crop monitoring platforms.
2. Innovators and tech companies should focus on creating low-cost, user-friendly AI tools tailored for small-scale agriculture in developing regions.
3. It encourages partnerships between governments, private tech firms, and agricultural cooperatives to pilot and deploy AI technologies at scale.

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