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Artificial intelligence and the future of food security in Nigeria

La inteligencia artificial y el futuro de la seguridad alimentaria en Nigeria

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Abstract. Food insecurity remains persistent in Nigeria despite abundant agricultural potential, driven by low productivity, weak infrastructure, and climate shocks. As global agricultural systems increasingly adopt Artificial Intelligence (AI) for forecasting, crop monitoring, and pest detection, this study examines its relevance for Nigeria's smallholder-dominated sector. A qualitative systematic review of 34 studies, identified through Scopus, Web of Science, PubMed, and Google Scholar and screened using a PRISMA approach, synthesised evidence on AI applications, food security dimensions, and adoption barriers. Findings show that while AI has improved yields and reduced costs in countries such as India, China, and Kenya, adoption in Nigeria remains minimal due to poor connectivity, low digital literacy, high costs, and weak policy coordination. The review highlights the need for localized, low-bandwidth, farmer-friendly AI tools and stronger data governance. It concludes that with improved rural infrastructure, capacity building, and support for local innovation, AI can significantly enhance Nigeria's food security.

Keywords. Artificial Intelligence, Food security, Digital Agriculture, Nigeria

Resumen. La inseguridad alimentaria persiste en Nigeria a pesar de su abundante potencial agrícola, debido a la baja productividad, la debilidad de las infraestructuras y las crisis climáticas. A medida que los sistemas agrícolas mundiales adoptan cada vez más la inteligencia artificial (IA) para la previsión, la supervisión de cultivos y la detección de plagas, este estudio examina su relevancia para el sector nigeriano, dominado por pequeños agricultores. Una revisión sistemática cualitativa de 34 estudios, identificados a través de Scopus, Web of Science, PubMed y Google Scholar y seleccionados mediante un enfoque PRISMA, sintetizó las pruebas sobre las aplicaciones de la IA, las dimensiones de la seguridad alimentaria y las barreras para su adopción. Los resultados muestran que, si bien la IA ha mejorado los rendimientos y reducido los costos en países como India, China y Kenia, su adopción en Nigeria sigue siendo mínima debido a la mala conectividad, los bajos niveles de alfabetización digital, los altos costos y la débil coordinación de políticas. La revisión destaca la necesidad de herramientas de IA localizadas, de bajo ancho de banda y fáciles de usar para los agricultores, así como una gobernanza de datos más sólida. Concluye que, con la mejora de la infraestructura rural, el desarrollo de capacidades y el apoyo a la innovación local, la IA puede mejorar significativamente la seguridad alimentaria de Nigeria.

Palabras clave. Inteligencia Artificial, Seguridad Alimentaria, Agricultuta Digital, Nigeria.

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INTRODUCTION

Food security remains one of the most pressing challenges for nations globally, particularly in developing countries such as Nigeria. Food security is defined as a condition in which all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life (World Food Summit, 1996). In many African countries, insufficient access to food continues to pose significant risks, with crises in Somalia, Ethiopia, and parts of Kenya illustrating the potential consequences.

Nigeria's food insecurity arises from multiple, interconnected challenges. Food availability, or the supply of food through domestic production or imports, is constrained by low agricultural output, inefficient policies, corruption, civil insecurity, and climate change. Despite agriculture employing a large portion of the workforce and Nigeria's vast arable land and favorable agro-ecological zones, local production often falls short of demand, making the country heavily reliant on imports such as rice and wheat.

This dependence increases vulnerability to global market fluctuations and destabilizes food availability and affordability. Food accessibility, the ability of households to obtain adequate food, is further limited by rising poverty, income inequality, and high food prices, while poor infrastructure and insecurity restrict distribution to remote communities (Rahman et al., 2023). These systemic challenges contribute to widespread malnutrition, highlighting that food insecurity in Nigeria concerns not only production but also distribution and utilization.

Over the last two decades, there has been growing recognition of the potential for technological innovations to address persistent agricultural challenges and strengthen food security. Traditional interventions, including mechanization, improved seed varieties, and irrigation systems, have provided incremental benefits but have not fully mitigated the structural issues contributing to food insecurity (FAO, 2021; Eme *et al.*, 2014).

In this context, Artificial Intelligence (AI) defined as computer-based systems capable of performing tasks that typically require human intelligence, such as prediction, pattern recognition, and decision-making has emerged as a transformative tool for agriculture. Globally, AI is applied to provide predictive analytics, monitor crop health, and improve supply chain efficiency, often demonstrating measurable impacts on yields, costs, and resilience (Javaid *et al.*, 2023; Rangrej *et al.*, 2023; Liu *et al.*, 2021).

Despite these advances, AI adoption in Nigeria remains limited. Research and innovation in the Nigerian agricultural sector continue to emphasize conventional approaches, with minimal attention to AI-driven solutions (Akinola *et al.*, 2022). Contextual differences between Nigeria and countries that have successfully deployed AI, such as India, China, and the United States, are substantial. These countries benefit from advanced infrastructure, robust financial systems, and high digital literacy, whereas over 70% of Nigerian farmers are smallholders with limited access to credit, weak connectivity, and minimal exposure to digital technologies (World Bank, 2022). These disparities highlight the need to explore how AI can be adapted to low-resource environments with infrastructural deficits, affordability constraints, and socio-cultural considerations.

Limited scholarship examines AI as a transformative tool in Nigerian agriculture, and most studies on AI in agriculture focus on contexts with advanced infrastructure, digital literacy, and financial systems (Akinola *et al.*, 2022; FAO, 2021; Eme *et al.*, 2014; Rangrej *et al.*, 2023; Liu *et al.*, 2021). Consequently, the applicability of global evidence to Nigeria is uncertain. Field-level insights into how AI tools such as weather prediction, pest detection, or soil monitoring perform in local farming contexts are scarce.

Moreover, equity issues, including the potential exclusion of women, smallholders, and marginalized populations from AI benefits, remain largely unexplored (Clapp *et al.*, 2022). This gap underscores the need for studies that systematically review existing knowledge, explore contextual adaptation strategies, and provide actionable recommendations to ensure AI enhances food security inclusively in Nigeria.

Study Objectives

Accordingly, this study aims to: 1) Systematically review and synthesize existing knowledge on the application of AI in Nigerian agriculture, focusing on its potential to enhance food security, 2) Examine the types of AI interventions currently explored in agricultural research, 3) Assess the applicability and effectiveness of AI tools in local Nigerian farming contexts, 4) Identify gaps in empirical evidence, particularly regarding equity and access for women, smallholders, and marginalized populations and 5) Provide recommendations for adapting AI technologies to Nigeria's unique agricultural systems.

To address the research gaps identified above and achieve the study objectives, the next section describes the methods used to systematically gather and analyse relevant evidence

MATERIALS AND METHODS

This section describes the methodological processes used in this study. It is organized into seven subsections.

Research design

This study adopts a qualitative systematic literature review and analytical research design, which is appropriate for synthesizing existing evidence on the intersection of Artificial Intelligence (AI) and food security in Nigeria. A literature review was chosen because it enables the identification of patterns, gaps, and critical insights from previous studies without collecting new primary data (Snyder, 2019). This design is particularly relevant since AI in agriculture is an emerging field in Nigeria, where empirical research remains limited (Akinola *et al.*, 2022).

Data sources

The study relied entirely on secondary data, drawn from peer-reviewed journal articles, policy reports, and official documents from international organizations such as the Food and Agriculture Organization (FAO), the World Bank, and the International Food Policy Research Institute (IFPRI). To ensure credibility, only articles published in reputable journals, books, and reports were included. Following recommendations by Cooper (2016) and Kitchenham *et al.* (2009).

Search strategy

The data collection process followed a structured and comprehensive search strategy across four major academic databases: Scopus, Web of Science, PubMed, and Google Scholar. The search covered publications from 2006 to 2024 and employed Boolean operators (AND/OR) to combine keywords related to Artificial Intelligence, digital agriculture, and food security in Nigeria.

Keywords were first grouped into concept clusters, such as Artificial Intelligence, Agriculture, and Food security and then systematically combined. For example, terms such as "Artificial Intelligence" AND "Nigerian agriculture", "AI" AND "food security", "digital farming innovations" AND "Nigeria", and "AI adoption challenges" AND "developing countries" were used in various combinations. Database-specific search strings were adapted to the syntax requirements of each platform. In Scopus, field tags such as TITLE-ABS-KEY were used to locate keywords in titles, abstracts, and keywords.

Web of Science employed the TS= topic field, while PubMed required the use of MeSH terms combined with free-text keywords. Google Scholar required broader search expressions, with the most relevant results manually screened from the first 200 entries. The complete search strings used in each database is presented in appendix 2

Inclusion and exclusion criteria

To maintain quality and relevance, studies were selected based on the following criteria: studies published in English, studies addressing AI, digital technologies, or food security in Nigeria or comparable developing countries, peer-reviewed journal articles, books, conference papers, and credible reports.Articles without clear empirical or theoretical contributions were excluded, publications older than 18 years were excluded, unless seminal, duplicated or non-English materials were also excluded.

Study Selection

The initial search yielded a total of 66 articles, which were gotten across the databases as follows: 13 from Scopus, 17 from Web of Science, 26 from Google Scholar, and 10 from PubMed. All retrieved records were exported into a reference management system for organization and screening. After going through the 66 manuscript, 12 duplicates were removed, leaving 54 unique studies for initial assessment. Title and abstract screening resulted in the exclusion of 8 studies that did not meet the predefined criteria, leaving 46 studies eligible for full-text evaluation. During full-text screening, an additional 12 studies were excluded because full manuscripts could not be accessed. Ultimately, 34 studies met all inclusion criteria and were retained for the final systematic review. A PRISMA flow diagram illustrating the identification, screening, eligibility, and inclusion process is presented in Figure 1

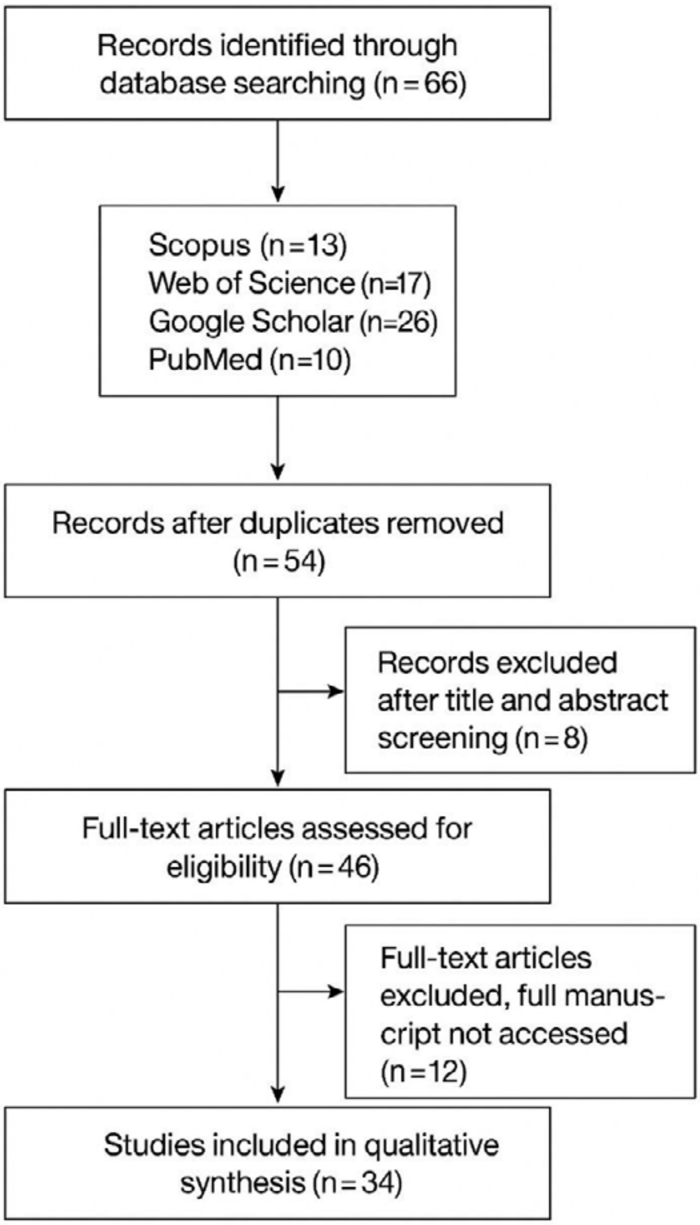

Figure 1. A flow diagram illustrating the identification, screening, eligibility, and inclusion process

Data extraction

A standardized data extraction form was developed prior to the review, drawing on the recommendations of Cooper (2016) and Kitchenham *et al.* (2009). This form served as a uniform template for recording essential details from each study, including bibliographic information, study design, methodological approaches, type of AI technology discussed, and major findings.

The author performed the initial extraction by carefully reading each of the 34 included studies and entering the relevant information into the standardized form. To enhance the reliability and credibility of the extraction process, two independent reviewers subsequently examined all extracted entries. They cross-checked the information against the original full-text articles to verify its accuracy, completeness, and alignment with the inclusion criteria. Any discrepancies or ambiguities identified during this process were resolved through discussion until consensus was reached.

Following verification, the extracted data were consolidated into a single dataset, which allowed for systematic comparison and thematic categorization during the analysis phase. This structured and highly controlled extraction process ensured that the synthesis of evidence was both transparent and methodologically sound, thereby strengthening the validity of the review's conclusions.

A table of characteristics of included studies (author, year, country, design, sample, main findings) is presented in appendix 1.

Data analysis

The data were analysed using a narrative synthesis approach due to the methodological heterogeneity across the included studies therefore, no statistical pooling or meta-analysis was conducted, Instead, findings were compared descriptively across categories such as AI applications in agriculture, the current state of food security in Nigeria, and the barriers influencing AI adoption.

Studies that addressed AI applications were synthesised by grouping technologies into categories such as machine learning, remote sensing, robotics, expert systems, and digital advisory platforms. For food security related studies, the dimensions of food availability, accessibility, utilisation, and stability were used as analytical lenses to compare how different authors conceptualised the challenges facing Nigeria. Barriers to AI adoption were analysed by extracting all recurrent themes, including infrastructural deficits, cost of technology, digital literacy, policy limitations, and socio-economic constraints. Where studies provided comparative insights or case experiences from other countries such as India, these were integrated narratively to highlight transferable lessons and contextual differences.

The narrative synthesis approach allowed the findings to be integrated into broader thematic patterns.

Study limitations

The review was limited to studies published in English, which may have excluded relevant research in other languages. Articles that could not be accessed in full were also excluded, potentially omitting valuable findings. Additionally, only publications from the last 16–18 years were considered, which may limit insights from older studies but allowed the review to focus on more recent developments.

Following a systematic search, and sreening process, The results are presented in the section below

RESULTS

This section presents the study findings and is organized into four subsections

Literature Characterisation: 34 Studies Across 5 Regions

A total of 34 studies were included in this review, representing 5 geographical regions (Nigeria, Africa, Europe, Asia, and global studies). Of these, 7 studies focused on Nigeria, 4 on other African countries, 2 on Europe, 3 on Asia, and 18 had a global scope as illustrated in figure 3. The majority were reviews or conceptual analyses (n = 23), followed by empirical or impact assessment studies (n = 3) and policy reports (n = 8) as illustrated in figure 2.

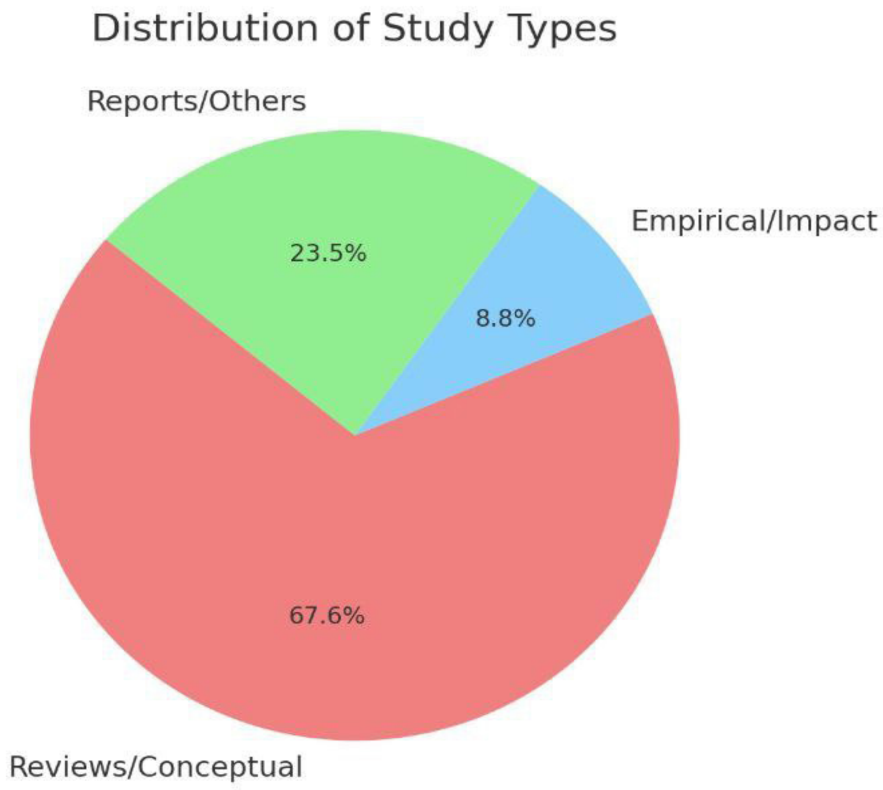

Figure 2. Distribution of study types included in the review, showing the proportion of reviews, empirical studies, and reports.

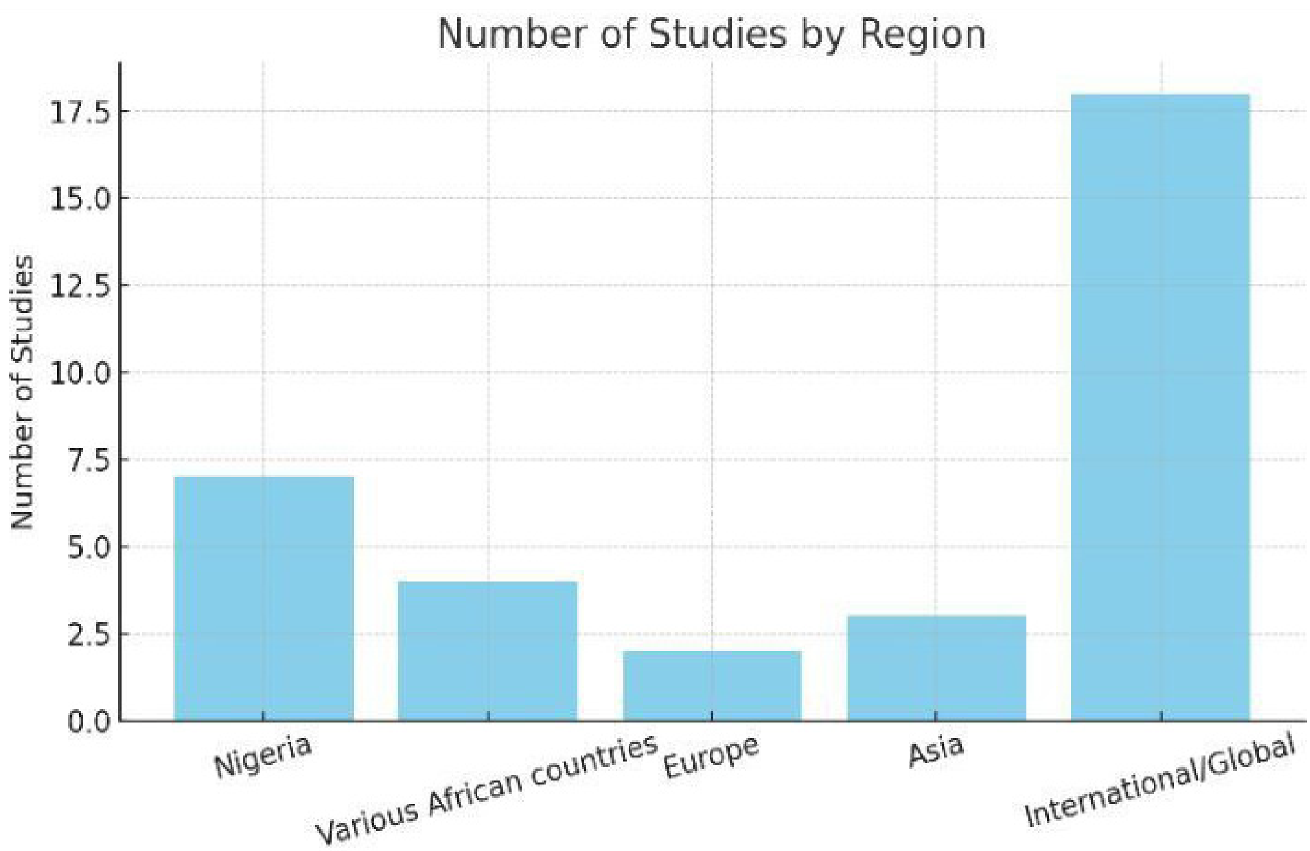

Figure 3. Number of literature reviews across different regions, illustrating regional contributions to the research base

Food Security Pillars

Food availability: Several studies found that despite Nigeria's fertile land, local food production is inadequate to meet demand. For example, Elijah (2019) noted that inconsistent policies and low mechanization have limited production, while Ogundeji et al. (2020) reported that smallholder rice farmers still experience low yields due to labor bottlenecks and inefficient farming methods. Adelekan and Omotayo (2021) found that digital agriculture has potential to improve productivity, but poor infrastructure and high costs currently constrain adoption.

Food accessibility: It was found that many households face economic, physical, and social barriers to accessing food. Nwajuibe (2012) highlighted poor infrastructure and low investment as key obstacles, while Matemilola and Elegbede (2017) emphasized that poverty and weak governance exacerbate access issues. Shepherd et al. (2020) reported that digital platforms can improve market linkages and reduce transaction costs, but adoption remains limited by literacy and connectivity challenges.

Food utilization: Studies indicated that utilization is compromised by poor diet diversity and food safety issues. Rahman *et al.* (2023) observed that even when food is available, malnutrition persists due to reliance on carbohydrate-rich staples and limited access to clean water. AI applications in soil monitoring, crop quality assessment, and livestock health were identified as tools that can enhance nutritional outcomes (Ryan *et al.*, 2023; Smith *et al.*, 2021; Oyedele *et al.*, 2021).

Food stability: Stability was found to be highly vulnerable to climate shocks, insecurity, and price fluctuations. FAO (2021) and WMO (2023) reported that recurrent droughts, flooding, and extreme heat events disrupt production cycles. Javaid *et al.* (2023) and Rangrej *et al.* (2023) found that AI-powered forecasting and early warning systems can enhance resilience, but such tools are not yet widely implemented in Nigeria.

AI Applications in Agriculture

It was found that AI can improve weather prediction, crop and soil monitoring, disease detection, irrigation management, and livestock health. For example:

Weather forecasting: Javaid *et al.* (2023) reported that AI systems integrating satellite and sensor data provide accurate localized forecasts, which are crucial for rain-dependent Nigerian agriculture. Without these systems, smallholder farmers remain highly vulnerable to unpredictable rainfall.

Plant disease and pest detection: Barbedo (2019) found that deep learning models can detect leaf lesions with high accuracy. In Nigeria, Akinola *et al.* (2022) noted that widespread pests such as cassava mosaic virus and fall armyworm significantly reduce yields, and AI-based detection could help manage outbreaks.

Soil and crop monitoring: Ryan *et al.* (2023) and Liakos *et al.* (2018) found that AI systems using sensor data can recommend precise fertilizer and irrigation schedules. However, Adelekan and Omotayo (2021) noted that lack of technical knowledge and access to digital tools in Nigeria limits practical adoption.

Precision irrigation: Bacco *et al.* (2019) and Liu *et al.* (2021) reported that AI-driven irrigation reduces water wastage by up to 50%, yet in Nigeria, less than 5% of arable land is irrigated, making this application largely unrealized (Li *et al.*, 2022).

Crop cultivation and harvesting: Liu *et al.* (2021) observed that AI can guide planting density and harvest timing. Ogundeji *et al.* (2020) noted that delayed harvesting remains a major issue in Nigeria due to labor shortages, highlighting the potential role of AI-assisted tools.

Greenhouse automation: Xu et al. (2020) found that AI-managed greenhouses increase yields and reduce energy consumption. Nigerian studies (Oyedele *et al.*, 2021; Shepherd *et al.*, 2020) indicate that urban greenhouse adoption is constrained by cost and technical expertise.

Livestock management: Rahman *et al.* (2023) and Smith *et al.* (2021) found that AI tools can monitor animal health, predict disease outbreaks, and optimize feeding. However, widespread implementation is limited in Nigeria by affordability and awareness issues.

Table 1 below is the key artificial Intelligence applications in Nigerian agriculture

Table1. AI applications in Nigerian Agriculture

AI Application	Function
Weather Forecasting	Provides localized climate predictions to guide planting and irrigation.
Pest and Disease Detection	Detects crop diseases and pest infestations early to reduce yield losses.
Soil and Crop Monitoring	Monitors soil moisture, fertility, and crop health, and recommends fertilization and irrigation schedules.
Precision Irrigation	Optimizes water usage and reduces wastage in irrigation systems.
Crop Cultivation and Harvesting	Guides planting density, sowing schedules, and harvest timing to maximize yields
Greenhouse Automation	Controls environmental conditions to optimize plant growth and reduce energy consumption
Livestock Management	Monitors animal health, predicts disease outbreaks, and optimizes feeding and productivity.

Table 2. Comparative table of barriers vs Nigeria current status vs successful countries

Barriers	Nigeria's Current Status	Successful Countries(Facilitator/ Enabler)
Infrastructure	Poor internet coverage and unreliable electricity	Widespread mobile networks and improved rural electricity access support AI-driven advisory platforms like Microsoft–ICRISAT Sowing App in India and China
Digital Literacy	Low digital literacy among farmers and extension officers prevents effective use of digital platforms and AI tools.	India: Government and NGO-led training programs equip farmers to use mobile apps for planting recommendations. China: Farmers and extension officers receive technical training to operate AI-enabled greenhouse and soil monitoring systems.
Financial Access	High costs of AI tools and limited access to credit restrict adoption among smallholder farmers	India: Subsidies and affordable digital agriculture solutions lower the financial barrier for farmers to adopt AI-based tools. China: Access to low-interest loans and government support allows farmers to invest in AI-enabled irrigation and greenhouse systems.
Policy and Governance	Agricultural policies are fragmented, with weak coordination and limited integration of AI initiatives.	India: National strategies integrate digital agriculture into the broader food security framework, providing clear guidelines and incentives China: Coordinated policies support smart agriculture programs and adoption of AI at provincial and national levels.
Technology Adoption	Resistance due to traditional farming practices and low awareness slows uptake of new technologies	India: Early adoption encouraged via user-friendly apps and farmer incentive programs. China: Farmers adopt AI technologies due to government demonstration farms and hands-on training.

Global Case Studies

It was observed that countries such as India, China, Brazil, and Kenya offer valuable lessons. In India, the Microsoft–ICRISAT Sowing App enabled farmers to increase yields by up to 30% through AI-driven planting recommendations (Rangrej *et al.*, 2023). Similarly, CropIn and Fasal platforms improved soil monitoring and pest detection, lowering input costs by 15–20% (CropIn, 2024).

In China, Liu *et al.* (2021) found that AI combined with IoT enhanced greenhouse management, reducing fertilizer use by 30% while improving yields. In Brazil, Marvin *et al.* (2022) reported AI applications in pest detection and supply chain optimization, which reduced losses and strengthened food distribution. In Kenya, mobile-based platforms like Hello Tractor and Digital Green improved mechanization and smallholder advisory services (Shepherd *et al.*, 2020).

Below is a comparative table of Barriers vs. Nigeria current status vs. successful countries (Facilitator/ Enabler) to visualize gaps

Having presented my findings, the following discussion interprets these findings, situating them within the broader literature and exploring their implications for food security and policy.

DISCUSSION

This section interprets the findings in relation to existing literature and policy implications. It is organized into nine subsections

Literature Characterization and Research Landscape

The review revealed that most studies on AI in agriculture were conceptual or review-based, with very few employing empirical methods. This suggested that the field in Nigeria was still in its nascent stages, with limited evidence of real-world implementation. The predominance of global and non-African studies highlighted a research gap in locally contextualized AI applications. Studies focused on Nigeria consistently reported that digital agriculture adoption was low due to limited infrastructure, funding gaps, and insufficient farmer awareness (Akinola *et al.*, 2022; Adelekan & Omotayo, 2021). These findings suggested that Nigerian agricultural research had not yet progressed to robust field-level experimentation, leaving policymakers with little empirical guidance for AI-driven interventions.

Implications of AI Adoption in Nigerian Agriculture

Despite its limited uptake, AI was recognized as a transformative tool capable of improving efficiency, productivity, and resilience. The discussion suggested that early-stage adoption was constrained not by technological limitations but by systemic and socio-economic barriers. For instance, smallholder farmers often lacked access to smartphones, sensors, and stable internet, which prevented the application of even basic AI tools. International examples illustrated that AI adoption could dramatically enhance crop management and yield forecasting when contextualized appropriately (Rangrej e*t al.*, 2023; Liu *et al.*, 2021). This indicated that Nigeria's agriculture sector could benefit from carefully tailored AI interventions that take into account resource limitations, socio-cultural practices, and local crop systems.

Another key implication of the findings was that effective AI deployment in Nigerian agriculture depended on significant localization to smallholder conditions. Since most farmers cultivated less than three hectares, AI tools required adaptation to local crop varieties, soil types, pest pressures, and farming calendars. They also needed to function on basic mobile devices, provide offline or low-bandwidth options in areas with weak connectivity, and present advisory information in simplified formats and local languages for users with limited digital literacy. Without these contextual modifications, many AI innovations remained poorly aligned with the operational realities of Nigerian smallholders, which limited their usability and adoption.

Barriers to Technology Uptake

Multiple interrelated barriers limited AI integration. Economic constraints, low digital literacy, and poor connectivity were primary obstacles for smallholder farmers, while cultural factors and reliance on traditional farming methods reinforced resistance to technological change

(Shepherd *et al.*, 2020; Ogundeji *et al.*, 2020). The discussion suggested that technology adoption was not merely a matter of tool availability but required simultaneous efforts in training, community engagement, and trust-building.

Furthermore, the findings also aligned with the three-level digital divide framework, which explained why connectivity remained a critical barrier to AI adoption in Nigeria's rural areas. The access divide was evident in weak broadband coverage, poor electricity supply, and low smartphone ownership across rural communities. The skills divide reflected limited digital literacy, which reduced farmers' ability to interpret or apply AI-generated recommendations. Finally, the outcomes divide showed that even when rural farmers accessed digital tools, the benefits were far lower than those observed in countries such as India or China, where stronger rural infrastructure enabled more effective AI deployment. This framework therefore illustrated that Nigeria's AI adoption challenges were rooted not merely in technology availability but in persistent structural inequalities between urban and rural digital environments.

Lessons from International Experiences

The experiences of India, China, Brazil, and Kenya illustrated that AI can enhance productivity, reduce losses, and optimize resource use when properly implemented. AI-driven solutions for pest detection, soil management, and irrigation were reported to improve yields and reduce input wastage significantly (Rangrej *et al.*, 2023; Marvin *et al.*, 2022; Shepherd *et al.*, 2020). These cases emphasized the importance of local adaptation, stakeholder partnerships, and supportive policy environments. For Nigeria, the lesson was that direct technology transfer without contextualization would likely fail, whereas designing solutions that account for smallholder constraints, seasonal variations, and socio-economic realities could enable more sustainable adoption.

Cost Opportunity Analysis Agricultural AI Investment versus Rural Infrastructure

By comparison, agricultural AI applications including precision farming, predictive irrigation, and disease monitoring depend heavily on a functioning infrastructural base and digital ecosystem to deliver measurable outcomes (Akbar *et al.*, 2023; Li, Ma, & Xu, 2022; Ryan, Peschl, & McNamara, 2023). In contexts where connectivity is weak and electricity supply is unreliable, the benefits of AI adoption are constrained, and returns on investment are delayed or diminished.

This juxtaposition highlights a critical insight: while AI promises transformative gains for productivity and efficiency, the opportunity cost of allocating scarce resources to AI without first strengthening rural infrastructure may limit its effectiveness. Accordingly, a sequenced or integrated approach where basic infrastructural improvements are prioritized and complemented by gradual AI integration appears more likely to yield meaningful and equitable gains for smallholder farmers. This discussion reinforces the need for policymakers to balance technological innovation with foundational rural development, ensuring that investments in AI do not occur in isolation but build upon an enabling environment capable of supporting sustainable agricultural growth.

Urban–Rural Contrast in AI Adoption in Nigeria

While AI adoption in agriculture remained limited, Nigeria had recorded significant success in deploying AI-driven solutions in urban sectors, particularly fintech, telecommunications, and digital services. Fintech platforms such as Flutterwave, Interswitch, and Moniepoint routinely used AI for fraud detection, transaction routing, and customer analytics. Similarly, telecommunications firms such as MTN and Airtel integrated AI to optimise network performance, automate customer service, and analyse consumer behaviour.

These urban-sector achievements demonstrated that Nigeria did not suffer from a national technological deficit. Instead, the barriers to agricultural AI adoption were largely rural and structural, rooted in limited connectivity, infrastructure gaps, low digital literacy, and the socio-economic constraints of smallholder farming communities. This contrast showed that the issue was not whether Nigeria could adopt AI, but whether rural systems possessed the structural capacity to support such innovation.

Agricultural Data Governance and Privacy in Nigeria

The expansion of agricultural AI in Nigeria brings significant data governance and privacy challenges. AI systems collect extensive farm-level and supply-chain data, including information on crop production, soil management, irrigation, and inputs (Adelekan & Omotayo, 2021; Shepherd, Turner, & Maas, 2020). In Nigeria, however, there are no comprehensive regulatory frameworks governing the collection, storage, or use of such data. This absence exposes farmers to risks such as unauthorized access, commercial exploitation, and unequal distribution of AI-enabled insights, which can undermine trust in digital agricultural technologies and limit adoption among smallholder farmers (World Bank, 2022).

To ensure sustainable AI adoption, context-specific data governance models are essential. These frameworks should establish clear standards for data ownership, privacy protection, consent, and ethical use while promoting equitable access to AI tools (Akbar et al., 2023; Ryan, Peschl, & McNamara, 2023). Collaboration among policymakers, technology providers, and research institutions is critical to develop these frameworks. Without robust governance, the transformative potential of AI in Nigerian agriculture may be compromised by ethical, legal, and social concerns, limiting both productivity gains and smallholder empowerment.

Risks of Foreign Technological Dependence in Nigeria's Agricultural AI Adoption

A critical concern in the adoption of agricultural AI in Nigeria is the growing risk of dependence on foreign technologies, particularly those developed in countries like India and China, which dominate the production of low-cost sensors, predictive analytics tools, and farm-management platforms. While these technologies offer tested functionalities and relatively affordable entry points, relying on them without parallel investments in Nigerian technical capacity creates structural vulnerabilities. Such dependence can limit Nigeria's ability to tailor AI systems to its unique agro-ecological, infrastructural, and socio-economic conditions, reducing the contextual effectiveness of imported models (Akbar *et al.*, 2023; Ryan, Peschl, & McNamara, 2023). It also raises concerns about long-term sustainability if updates, maintenance, and algorithmic improvements remain externally controlled.

Moreover, when foreign-built systems dominate the agricultural AI landscape, they often shape standards for data formats, pricing structures, system interoperability, and access to digital platforms. This imbalance can place Nigerian farmers, institutions, and even government agencies at a disadvantage, potentially leading to lock-in effects where switching to local alternatives becomes costly or technically impossible. In the long term, such dependence may hinder the development of Nigeria's domestic agri-tech ecosystem, weaken national control over emerging agricultural data infrastructures, and concentrate technological power in external actors who may not prioritise local food security objectives. Addressing these risks requires deliberate investment in local AI research, capacity building, and supportive policies that encourage indigenous innovation.

Policy Recommendations

Strengthening Rural Digital and Power Infrastructure:

A foundational step to enable AI adoption in Nigerian agriculture is the development of robust rural digital and power infrastructure. Currently, many smallholder farmers lack reliable internet access and consistent electricity, which prevents them from utilizing AI-driven advisory tools, weather forecasts, soil sensors, and mobile platforms. For a span of 2–5 years, the government should invest ₦80–₦250 billion to expand 4G and 5G networks into agricultural corridors, deploy fibre-optic backbones to underserved areas, and establish solar-powered digital hubs for off-grid communities. These interventions will provide the structural backbone required for the effective use of AI technologies, ensuring that both farmers and extension officers can access timely, data-driven guidance that directly improves productivity, pest management, and climate resilience.

Integrating Digital Agriculture Into National Food Security and Climate Policies:

To ensure coordinated AI adoption, digital agriculture must be embedded into Nigeria's national food security and climate frameworks. For a span of 12–18 months, an investment of ₦ 500 million– ₦ 2 billion should support the revision of key policies, such as the National Food Security Strategy and the Agricultural Promotion Policy, to incorporate AI-based advisory systems, climate-smart forecasting, and robust data-governance guidelines. This integration provides a clear institutional framework that aligns interventions across ministries, agencies, and development partners, allowing practical AI applications such as early warning alerts, crop monitoring, and market linkages to be effectively scaled and sustained nationwide.

Establishing National AI Extension and Farmer Training Programmes:

A critical barrier to effective AI deployment is the low digital literacy among both farmers and extension officers. Over the next 1–3 years, the government should allocate ₦5–₦15 billion to establish AI-focused training centres, conduct regional workshops, and develop mobile learning modules for extension services and farmers. These programmes should equip extension officers to interpret AI outputs and translate them into locally relevant guidance, while farmers receive practical training in using digital tools on the farm. By combining structured capacity building with technology deployment, these interventions will ensure that AI adoption moves from theoretical potential to real-world improvements in productivity, pest management, and irrigation efficiency.

Supporting Local Innovation Ecosystems and Private-Sector Participation:

Nigeria currently lacks sufficient domestic capacity to develop AI tools tailored to local agricultural contexts. To address this, within 1–2 years, the government should launch innovation grants, incubation hubs, and research industry partnerships, with annual funding of ₦10–₦30 billion. These measures will encourage the private sector and academic institutions to design affordable, context-specific AI solutions and generate empirical field data to guide deployment. By strengthening local innovation ecosystems, smallholder farmers will gain access to practical, cost-effective tools suited to Nigeria's crops, soils, and climatic conditions, thereby improving adoption rates and maximizing impact.

CONCLUSIONS

This review demonstrates that AI can significantly enhance productivity, climate resilience, and food security in Nigeria, but adoption remains constrained by poor digital infrastructure, low technical skills among farmers and extension officers, and weak policy support. To translate AI's potential into impact, Nigeria must prioritize expanding rural connectivity and reliable power, implement targeted AI training programmes for farmers and extension services, and support locally tailored digital agriculture solutions. Strengthening these foundations will enable the effective use of AI tools for pest management, yield monitoring, irrigation optimization, and early-warning systems, providing a clear, actionable pathway to improve agricultural productivity and food security within the next 5–10 years.

ARTIFICIAL INTELLIGENCE USE

ChatGPT (OpenAI) was used to structure and organize the manuscript, in line with the journal's ethical guidelines. All ideas, interpretations, and final decisions in the paper remain entirely in the Author.

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Appendix 1

N/A	Author	Year	Country	Design	Sample	Main Findings
1	Adelekan,S. A.;&Omotayo, A. O.	2021	African Countries	Review / conceptual analysis	N/A	Digital agriculture can improve productivity, and information access, adoption constrained by poor infrastructure, low literacy, cost, weak institutions, and policy gaps.
2	Akbar,A.;Anwar,M.; Shah, M.A.; & Alotaibi, F.	2023	International	Comprehensive review	N/A	AI improves precision farming, disease detection, yield prediction, and resource optimization. Challenges include limited datasets, interoperability, high costs
3	Akinola, O.; Adegbite, A.; & Okunlola, A	2022	Nigeria	Review / descriptive	N/A	AI adoption in Nigeria is early-stage; potential in crop monitoring, irrigation, pest detection. Barriers: infrastructure, awareness, funding, weak extension services. Recommends policies and capacity building
4	Bacco, M.; Barsocchi, P.; Ferro, E.; Gotta, A.; & Ruggeri, M.	2019	Europe	Survey / review	N/A	Digital technologies (IoT, WSNs, drones, cloud) enable smart farming; challenges: connectivity, energy, cost, interoperability
5	Barbedo, J. G. A	2019	Global	Empirical / deep-learning study	Leaf lesion image datasets	Deep-learning models classify plant diseases accurately at lesion level, improving detection versus whole-leaf analysis. Useful for plant pathology monitoring
6	Benos,L.; Tagarakis, A. C.; Dolias, G.; Berruto, R.; Bochtis, D.; & Busato, P.	2021	Europe / International	Review	N/A	ML improves precision agriculture in classification, prediction, robotics, yield estimation, and weed/pest detection. Challenges: data scarcity, model generalization, low real-farm adoption.
7	Carter, H.	1989	International	Review / conceptual	N/A	Discusses balancing traditional and modern agriculture; examines global food system shifts, policy effects, and sustainable transformation.
8	Clapp, J.; Moseley, W. G.; & Garrett, J.	2022	Global	Review / synthesis	N/A	Reviews progress and gaps in global food security; climate, conflict, inequality, and pandemics are major disruptors. Calls for resilient systems and policy interventions.
9	Elijah, I.	2019	Nigeria	Historical review	N/A	Historical overview of Nigerian agricultural programs (1960–2016). Highlights inconsistent policies, poor funding, weak monitoring. Food security remains elusive.
10	Eme, O. I.; Onyishi, T.; & Uche, O. A.	2014	Nigeria	Review / descriptive	N/A	Identifies threats to food security: insecurity, climate variability, corruption, infrastructure, poor financing, weak extension. Recommends governance strengthening and modern agricultural practices.

11	FAO	2006	Global	Policy brief	N/A	Defines four pillars of food security: availability, access, utilization, stability. Provides global conceptual and policy framework.
12	FAO	2012	Nigeria	Strategic planning document	N/A	Sets FAO priorities: productivity, value chains, natural resource management, nutrition, resilience. Identifies systemic constraints.
13	FAO	2021	Global	Annual report	N/A	Focuses on agrifood system resilience to shocks; recommends diversification, digitalization, governance reforms, climate-smart practices.
14	FAO	2022	Global	Global monitoring report	N/A	Rising global hunger/malnutrition due to conflict, climate change, pandemics. Advocates repurposed agricultural policies for affordable healthy diets.
15	Javaid, M.; Haleem, A.; Singh, R. P.; Suman, R.; & Rab, S.	2023	International	Review	N/A	Findings: AI supports monitoring, prediction, classification, automation: disease diagnosis, yield prediction, soil analysis, weed detection, robotics. Barriers: data, computation, adoption.
16	Li, D.; Ma, J.; & Xu, X.	2022	China	Review	N/A	AI models (ANNs, SVM, deep learning) improve irrigation scheduling, soil moisture forecasting, water-use efficiency. Challenges: generalization, real-time datasets, sensor integration.
17	Liakos, K. G.; Busato, P.; Moshou, D.; Pearson, S.; & Bochtis, D.	2018	International	Review	N/A	ML enhances decision-making in crop monitoring, livestock management, disease detection, greenhouse automation. Challenges: lack of standardization, poor datasets, limited adoption
18	Liu, Y.; Ma, X.; Shu, L.; Hancke, G. P.; & Abu-Mahfouz, A. M.	2021	International	Narrative / technical review	N/A	Transition from Industry 4.0 to Agriculture 4.0; enabling technologies: IoT, robotics, AI, big data, blockchain; research challenges: interoperability, security, scalability, cost, adoption.
19	Marvin, H. J. P.; Kleter, G. A.; & Bouwmeester, H.	2022	International	Review / conceptual	N/A	AI enhances food supply chain resilience: forecasting, logistics, waste reduction, quality monitoring. Challenges: data integration, transparency, regulation.
20	Matemilola, S.; & Elegbede, I.	2017	Nigeria	Review / policy	N/A	Drivers of food insecurity: poverty, governance, low productivity, post-harvest losses. Recommends multi-sector interventions.
21	Nwajuibe, C.	2012	Nigeria	Review / policy analysis	N/A	Identifies food security constraints: infrastructure, low investment, weak institutions, climate risks. Calls for strategic planning and governance improvements.
22	OECD	2020	Global	Policy report	N/A	Digital technologies enhance agricultural policy: data collection, monitoring, productivity, market efficiency. Challenges: data governance, literacy, infrastructure gaps.
23	Ogundeji, A. A.; Donkor, E.; & Onakuse, S.	2020	Nigeria	Empirical / impact assessment	Smallholder rice farmers	Mechanization improved productivity, reduced labor bottlenecks, and increased incomes. Constraints: finance, policy support, training.

24	Oyedele, O. A.; Akinbile, L. A.; & Oladosu, R. O.	2021	Africa	Review / conceptual	N/A	Digital technologies (IoT, AI, remote sensing) support sustainable soil management. Barriers: infrastructure, cost, technical skills.
25	Rahman, M. A.; Irfan, M.; & Alvi, S. H.	2023	International	Review	N/A	AI in livestock management: disease detection, feeding, behavior monitoring, production forecasting. Challenges: data, integration, awareness.
26	Rangrej, P.; Sharma, A.; & Patel, R.	2023	India	Empirical review / case study	N/A	AI improves yield prediction, disease management, precision farming. Challenges: high cost, low awareness, scalability
27	Ryan, M.; Peschl, M. F.; & McNamara, J.	2023	International	Review / conceptual	N/A	AI impacts innovation, sustainability, food security: precision agriculture, predictive analytics, supply-chain optimization. Adoption challenges: policy gaps, data quality, digital divide.
28	Shepherd, K.; Turner, J.; & Maas, B.	2020	Africa	Review / policy-focused	N/A	Digital agriculture can scale productivity and market linkages; barriers: infrastructure, capacity, policy. Recommends investment and enabling frameworks
29	Smith, D.; Jones, R.; & Brown, L.	2021	International	Review	N/A	AI improves animal health management via disease prediction, monitoring, diagnostic tools. Challenges: data, integration, low-resource adoption
30	Upton, J. B.; Cissé, J. D.; & Barrett, C. B.	2016	Multi-country	Conceptual / econometric	N/A	Proposes framing food security as resilience, integrating short-term access and long-term capacity; outlines measurement implications.
31	World Bank	2022	Africa	Policy / development report	N/A	Digital technologies can transform African agriculture, improving productivity, efficiency, market access; challenges: infrastructure, finance, literacy, policy support.
32	World Meteorological Organization (WMO)	2023	Global	Annual climate monitoring report	Global climate datasets	Reports 2022 climate anomalies affecting agriculture: extreme heat, drought, flooding; emphasizes adaptation needs.
33	Xu, X.; Li, Y.; & Zhang, W.	2020	China	Review / empirical synthesis	N/A	AI and IoT in greenhouses optimize environmental control, crop growth, and energy efficiency. Challenges: cost, integration, technical expertise.

34	Lajoie-O'Malley, A.; Bronson, K.; van der Burg, S.; & Klerkx, L.	2020	International	Policy review / document analysis	N/A	Analyzes digital agriculture and sustainable food system visions in policy frameworks. Opportunities for productivity, sustainability, innovation; gaps in inclusivity and implementation.

APPENDIX 2

Below is the complete search strategy in appendix showing exact terms and Boolean operators used in each database.

Scopus:

TITLE-ABS-KEY (artificial intelligence OR "AI") AND TITLE-ABS-KEY ("food security" OR "agriculture*" OR "digital farming") AND TITLE-ABS-KEY ("Nigeria")

Web of Science:

TS = (("artificial intelligence" OR "AI") AND ("food security" OR "digital agriculture" OR "precision farming") AND ("Nigeria" OR "Sub-Saharan Africa"))

PubMed:

("artificial intelligence" OR "AI") AND ("food security") OR "agriculture" OR "digital farming") AND ("Nigeria")

Google Scholar:

"artificial intelligence AND food security AND Nigeria"

and

"digital agriculture" OR "precision farming" AND "Nigeria"

and

"AI adoption challenges" AND "developing countries"

Grey literature including government policy documents, national agricultural strategy reports was also searched to capture practical applications not represented in peer-reviewed sources.