ARTIFICIAL INTELLIGENCE (AI) IN SUSTAINABLE AGRIBUSINESS IN NIGERIA: A NARRATIVE REVIEW OF INTEGRATED FRAMEWORKS

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Abstract
This narrative review evaluates the applications of AI technologies across Nigerian agribusiness, identifies systemic barriers. and synthesises data across the three core dimensions of sustainability: Economic Viability, Environmental Protection, and Social Equity. Utilising thematic synthesis, this study analyses contemporary literature and localized case studies on Agri-AI interventions to establish an integrated socio-technical framework tailored to Nigeria's agricultural infrastructure. The synthesis demonstrates that AI interventions deliver substantial multi-dimensional benefits: AI-driven predictive analytics and computer vision increase crop yields by 12% to 45%, reduce input expenditures by up to 25%, boost net farm profitability by 13% to 21%, and provide alternative credit scoring for unbanked producers. Smart soil sensors and automated precision irrigation achieve water savings of 30% to 50% in open fields (and over 60% in closed-environment agriculture), reduce nitrogen fertiliser leaching by up to 25%, and lower energy consumption while enabling predictive climate adaptation. Multimodal voice/USSD advisories and smartphone image diagnostics democratise agronomic advice for low-literacy farmers, expand credit access for female producers, and create technical employment for rural youth. To prevent technology from exacerbating rural inequality or displacing manual labor, the study proposes the Triple - P Agric AI Framework. This conceptual model harmonizes Economic Profitability, Environmental Resilience, and Social Inclusion, and serves as a strategic roadmap for policy makers, AgTech developers, and university-industry partnerships to drive equitable agricultural transformation in Nigeria.
Keywords: *Artificial Intelligence, Sustainable Agribusiness, Precision Agriculture, Digital Agriculture, Food Security, Nigeria, Socio-Technical Framework, Triple-P Framework.*

1. Introduction and Sectoral Context

1.1 Demographic Imperatives and Sectoral Vulnerabilities

The contemporary global agribusiness sector operates at a critical juncture, balancing the compounding pressures of explosive population growth, climate change, land degradation, acute resource scarcity, and declining labor availability. Projections indicate that the global population will reach 9.6 billion people by the year 2050, necessitating a 70% expansion in global food production to avert catastrophic food shortages (FAO, 2019).

Nigeria stands at a pivotal demographic and economic crossroads. With its population projected to surpass 400 million by 2050 (World Bank, 2022), ensuring sustainable food security is an urgent priority. While agriculture remains a foundational pillar of the national economy, the sector continues to grapple with severe structural limitations.

Nigeria's agricultural sector is overwhelmingly dependent on rain-fed smallholder systems, with over 80% of crop farming relying directly on seasonal rainfall patterns (Asadu, 2015). This reliance leaves the country highly vulnerable to climate variability and erratic weather shocks. Altered rainfall onset timings, delayed wet seasons, prolonged droughts in northern agrarian belts, and destructive flooding along the Niger and Benue river basins directly destabilize cropping calendars (Adebola & Ibeke, 2023).

Unpredictable precipitation regimes alter soil moisture dynamics, aggravate nutrient leaching, and increase the incidence of localized pest and disease outbreaks. Compounding these environmental pressures, a deficit in micro-climate weather forecasting infrastructure leaves rural smallholders unable to proactively adjust planting windows or hedge against climate shocks (Adebola & Ibeke, 2023; Samaila, 2025).

Post-Harvest Losses (PHL)

Post-harvest loss represents a substantial structural drain on the Nigerian food system, with an estimated $9 billion worth of agricultural produce lost annually (Ugwukah, 2020). Total losses across the value chain range between 20% and 60% depending on the specific commodity.

While grain losses generally hover between 5% and 20%, highly perishable commodities such as fresh fruits, vegetables, and root crops (e.g., cassava and yam) suffer pre-market losses reaching 30% to 60%. These losses are primarily driven by inadequate farm-gate pre-cooling, non-standardized packaging, rudimentary handling, and a lack of localized, decentralized processing facilities (Ugwukah, 2020).

Infrastructural Deficits

Infrastructural shortfalls create a barrier between primary rural production zones and urban consumption centers. Fewer than 10% of fresh agricultural produce moves through a temperature-controlled cold chain in Nigeria (Oyediran et al., 2021; Adepoju, 2021). The shortage of solar-powered cold hubs at farm gates and cold-storage transport vehicles force smallholders to sell produce immediately after harvest, leaving them vulnerable to severe price markdowns by buyers.

Furthermore, deteriorated rural feeder roads extend transit times and cause mechanical vibration damage to perishable goods during transport. These logistical challenges are compounded by unreliable grid electricity, which increases the operating costs of running processing and cold storage facilities on diesel generators (Oyediran et al., 2021).

Supply Chain Fragmentation and Market Inefficiencies

The Nigerian agricultural supply chain is spatially unbalanced and organizationally fragmented. Primary agricultural production, particularly for fresh produce and staple grains, is heavily concentrated in the northern geopolitical zones, whereas high-density consumer markets reside predominantly in the south. Transporting food across these geographic distances requires navigating fragmented logistics networks (Groot et al., 2021; Mhlanga, 2021).

Value chains are dominated by multiple tiers of informal brokers and middlemen. This structural setup inflates final consumer prices while keeping farm-gate compensation low. Moreover, a lack of real-time supply chain data and market intelligence prevents farmers from accurately forecasting demand, leaving them exposed to sudden market gluts and price crashes (Groot et al., 2021).

1.2 Policy Alignment and the Imperative for Ecological Decoupling

In response to these systemic hurdles, national policy pushes, such as the Draft Nigeria Digital Agriculture Strategy (NDAS), the National Agro-Productivity System (NAPS), and the Nigeria Agricultural Intelligence Platform (NAIP), reflect an institutional pivot toward data-driven, precision agriculture (Oyeyemi, 2022).

Historically, efforts to close the widening national food security gap relied on expanding cultivated land, increasing synthetic fertilizer application, and scaling traditional irrigation networks. However, this resource-extractive model has reached its ecological limits. Continued land clearing and chemical overuse accelerate soil depletion, widespread deforestation, severe water scarcity, and greenhouse gas emissions (Koneswaran & Nierenberg, 2008; Oertel et al., 2016; Rojas-Downing et al., 2017).

To achieve long-term sustainability, agribusiness must decouple production growth from environmental degradation. The convergence of Artificial Intelligence, big data, and digital technologies offers a viable pathway to achieve this decoupling by optimizing input efficiency and reducing overall resource intensity.

1.3 Technological Determinism vs. Socio-Technical Integration

Despite a growing library of technical pilots and strategic roadmaps, a significant divide remains between theoretical AI capabilities and their practical, long-term implementation across Nigerian agribusiness value chains. Many digital interventions operate as isolated pilots focusing heavily on algorithmic precision - such as soil sensor readings or yield predictions –

while treating technology as a plug-and-play solution.

Deploying AI algorithms in agriculture without an integrated socio-technical framework is like planting high-yield seeds in uncultivated soil: promising in theory, but vulnerable to structural failure (OECD, 2021).

This technological determinism often overlooks critical ground realities: rural digital illiteracy, inadequate power infrastructure, data sovereignty concerns, and deep-seated equity gaps. While existing literature documents the technical metrics of Agri-AI, there remains a need for qualitative, narrative-driven synthesis evaluating how integrated frameworks connect technology, human behavior, public policy, and environmental sustainability in Nigeria (Samaila, 2025; Olutumise, 2026).

2. Theoretical Foundations and Conceptualization of Artificial Intelligence

Understanding the application of AI in agriculture requires clear conceptual definitions. AI represents a suite of methods and technologies designed to perform tasks that historically required human intelligence, including visual perception, speech recognition, decision-making, and language translation. Artificial Intelligence is defined as a series of approaches, methods, and technologies that display intelligent behavior by analyzing their environments

and taking actions - with some degree of autonomy - to achieve specific objectives." Collier et al. (2017, cited in Cook and O'Neill, 2020).

Historically defined by Alan Turing as the engineering of intelligent machines, modern definitions emphasize adaptive capabilities. Kaplan and Heinlein characterize AI as a system's ability to correctly interpret data, learn from it, and apply those learnings to achieve specific goals through flexible adaptation (Pelicelli, 2023, cited in Bashir, 2025). Over the past decade, rapid advancements in machine learning (ML), deep learning (DL), data storage capacity, and high-performance cloud processing have enabled AI to transition from theoretical computer science into applied domain analytics across agricultural value chains (EPRS, 2019, cited in Cook and O'Neill, 2020).

3. Taxonomy of AI Applications across the Agribusiness Value Chain

AI integration across agricultural value chains can be categorized into five operational domains:

3.1 Predictive Analytics and Yield Forecasting

Predictive analytics leverages historical agro-climatic data, satellite imagery, and environmental variables to transition farming from reactive practices to proactive, data-driven management. Machine learning algorithms - such as Decision Tree Regressors, Random Forests, and Artificial Neural Networks (ANN) - analyze multi-layered datasets to forecast seasonal crop yields and optimize planting schedules (Ali et al., 2025; Habila et al., 2023; Tzachor et al., 2022).

By anticipating localized climate anomalies, precipitation changes, and drought risks, these predictive models enable smallholders and agribusiness managers to adjust resource allocation early in the production cycle. In Nigeria, crop yield prediction models using machine learning have demonstrated prediction accuracies exceeding 70%, providing a reliable foundation for national food security planning and farm-level risk management (Shuaibu, Obunadike, & Jamilu, 2024).

3.2 Computer Vision for Crop Health, Disease, and Pest Detection

Computer vision technologies, integrated with Deep Learning architectures such as Convolutional Neural Networks (CNNs) and Vision Transformers, are transforming crop protection practices. By processing high-resolution images captured via smartphones, Unmanned Aerial Vehicles (UAVs), or field cameras, computer vision systems perform real-time identification of plant diseases, nutrient deficiencies, and localized pest infestations (Adepoju et al., 2024).

Early diagnostic capabilities allow farmers to deploy targeted biopesticides or micro-doses of crop protection products. This targeted application avoids indiscriminate chemical spraying, protecting soil and surrounding aquatic ecosystems while lowering input costs for producers (Adepoju et al., 2024).

3.3 Smart Soil Intelligence and Precision Irrigation

The integration of AI with Internet of Things (IoT) sensor networks enables real-time monitoring of soil health and hydrological dynamics. Ground-based electronic probes measure soil parameter - including volumetric water content, pH, temperature, and nitrogen, phosphorus, and potassium (NPK) levels - and transmit this data directly to cloud-based analytics engines (Odirichukwu, 2024).

AI models analyze soil moisture thresholds and localized evapotranspiration rates to automate solar-powered precision irrigation systems. Water is delivered only when and where required, achieving water savings of 30% to 50% in semi-arid agrarian regions without compromising crop yields (Odirichukwu, 2024). Furthermore, remote spectral imaging and machine learning models analyze soil organic carbon and nutrient profiles rapidly, providing lower-cost diagnostics compared to traditional chemical laboratory testing (World Bank, 2024).

3.4 UAV Automation and Aerial Remote Sensing

Drones equipped with multispectral and hyperspectral sensors provide detailed monitoring of farm performance over broad geographic areas. AI algorithms process aerial imagery to construct Normalized Difference Vegetation Index (NDVI) maps, highlighting subtle variations in canopy health, crop biomass, and water stress before symptoms become visible to the human eye (Jha et al., 2019).

Furthermore, autonomous spray drones guided by AI flight paths apply fertilizers and crop protection treatments with centimeter-level precision (Santangeli et al., 2020; Roslim et al., 2021; Jung et al., 2021; Alghamdi et al., 2021; El-Hoummaidi et al., 2021). This targeted delivery minimizes chemical runoff into adjacent farm ecosystems and reduces worker exposure to hazardous agro-chemicals (Ahmed et al., 2023).

3.5 AI-Driven Agri-FinTech and Digital Supply Chains

AI applications extend beyond physical farm management to address systemic market and financial friction across agricultural value chains. They provide Alternative Credit Scoring through Agritech platforms that use machine learning to synthesize satellite imagery, farm boundary coordinates, and historical yield data, generating digital credit scores for unbanked smallholders (CGAP, 2023). This alternative risk scoring helps lower borrowing costs and improves access to formal credit for high-quality seeds and inputs.

Secondly, they provide Supply Chain Optimization & Price Transparency**:** Natural Language Processing (NLP) platforms and predictive market algorithms connect farmers directly with commercial buyers. By offering real-

time pricing intelligence, dynamic transport routing, and demand forecasting, these systems reduce post-harvest losses, limit exploitation by informal intermediaries, and improve producer margins (IFAD, 2024).

4. Current AI Landscape in Nigeria: Operational Applications and Platform Synthesis

AI in Nigerian agricultural space is evolving from theoretical research to practical tools for improvement of farm yields. Major trends comprise AI-supported precision farming for automated irrigation, remote monitoring of soil conditions, and disease risk mapping. Nonetheless, widespread use is constrained by low level of digital knowledge, exorbitant costs of internet connectivity, and inadequate infrastructure (Choruma, et al., 2024).

4.1 Localized Applied Trends

Crop and Pest Management in AgTech platforms leverage machine learning and satellite imagery to evaluate soil health and forecast pest outbreaks. Farmers utilize tools such as Crop2crop and Plantix to diagnose plant diseases directly from smartphone photo uploads (Muhammad, Usman, & Sani, 2025; Olawumi et al., 2025).

Automation and Mechanization provide digital solutions such as *Hello Tractor* combine IoT sensors and machine learning to optimize tractor fleet utilization and offer tractor-hailing services that connect smallholder farmers with nearby equipment owners (Olawumi et al., 2025).

Precision Farming in Agrarian Belts support Field studies which indicate that AI-supported automated irrigation systems minimize water waste by 20% to 35%. In Kaduna State, solar-powered IoT systems and machine learning analytics have driven crop yield increases ranging from 10% to 25% (Bisi et al., 2025; Olufemi, Bukola, & Bamidele, 2026).

Climate-Intelligent Extension Services in AI-driven advisory systems aggregate big data to recommend optimal seed varieties and planting dates tailored to localized soil profiles and weather forecasts (Dinrifo et al., 2022; Olusola-Ilori & Afolaranmi, 2025).

4.2 Emerging Localized Innovations.

To address local infrastructure constraints, several innovative delivery mechanisms have emerged:

Multimodal Data Integration can be achieved by **c**ombining soil sensors, weather data, and drone imagery to optimize resource usage. For instance, pilot projects in Kaduna demonstrated a 25% reduction in water usage for tomato cultivation (Krishnakumar & Shah, 2025; Ozor et al., 2025; Muhammad, Usman, & Sani, 2025)

Voice-Supported Advisory Services can be provided to overcome digital illiteracy by using platforms to deploy AI voice assistants that provide market updates and agronomic advice in native languages, including Hausa, Yoruba, Igbo, and Pidgin (Olawumi et al., 2025).

USSD/SMS Offline Models help to bypass high data costs and poor rural internet connectivity by using platforms to deliver AI advisory via USSD and SMS. For example, *Crop2Cash* utilizes its AI-powered hotlines to deliver automated voice advisories to over 500,000 rural producers (Samaila, 2025; Olufemi et al., 2026).

Computer Vision Disease Diagnostics are done by research organizations like the International Institute of Tropical Agriculture (IITA) that have integrated custom Cassava Disease Models into mobile applications like Plantix, enabling farmers to scan cassava leaves and receive instant diagnostic treatment plans (Muhammad et al., 2025).

Solar-Powered Edge IoT Devices have enabled institutions to operate independently of the national power grid by co-designing localized edge devices. A prominent example is the *University of Nigeria, Nsukka (UNN) Nsukka Yellow Pepper Project*, which deployed solar-powered Raspberry Pi cameras and text-based IoT systems to provide early warnings of localized pest attacks to female farmers (Olufemi et al., 2026).

4.3 Synthesis of Prominent AI Agricultural Platforms in Nigeria

The landscape of operational AI platforms in Nigeria highlights diverse functional applications across the value chain, as detailed in Table 1 below:

Table 1: AI Agriculture Platforms in Nigeria and their Functions

Platform Name	Primary AI Function	Technology Utilized	Target Challenge	Funding/Wort h (USD)	Reference
Kitovu	Agronomic Advisory	Remote Sensing	Soil health, yield optimization	Not publicly disclosed	Dinrifo et al. (2022)
AirSmat	Resource Optimization	Drones, Satellites, IoT Sensors	Water, fertilizer, pesticide efficiency	Not publicly disclosed	Dinrifo et al. (2022)
Apollo Agriculture	Financial Inclusion	Machine Learning, Satellite Imagery	Access to credit and insurance	$40 million raised in Series B (2022)	TechCrunc h (2022)
Babban Gona	Offline Farm Management	On-device ML models	Poor rural connectivity	$100 million+ investment secured (2021)	IFC (2021)

AgroCo	Pest/Nutrient Diagnosis	Image Recognition (Smartphone)	Disease identification, soil health	Not publicly disclosed	Ben Ayed & Hanana (2021)
Trace Genomics	Soil Analysis	Machine Learning	Soil nutrient status	$160 million valuation (2022)	Elbasi et al. (2022)
Sky Squrrel Technologies	Crop Health Monitoring	Drone based Aerial Imaging	Early disease detection	$25 million valuation (2022)	Singh & Kaur (2022)
Crop2Cash	Financial Inclusion & Produce Traceability	Mobile AI apps, Blockchain, ML	Access to credit, produce payments, traceability	$350,000 seed funding (2024)	Space in Africa (2024)
ReLeaf	Supply Chain & Processing Optimization	Computer Vision, ML, IoT Sensors	Low processing efficiency,	$3.3 million pre-Series A funding (2023)	TechCrunc h (2023)
Hello Tractor	Smart Mechanization & Predictive Maintenance	IoT, AI based demand prediction	Mechanization gaps, tractor underutilization	Estimated $12 million+ valuation (2022)	World Bank (2023)
Zenvus	Maintenance Precision Farming & Soil Mapping	Sensors, AI Analytics, GIS	Soil fertility mapping, yield optimization	Not publicly disclosed	Do4Africa (2023)

Source : (Samaila, 2025, p.20).

The table 1 shows that existing AI platforms in Nigeria focus considerably on advisory services, precision resource management, risk mitigation, offline functionality, financial inclusion and produce traceability, post-harvest inefficiencies, smart tractor-hailing and predictive maintenance services, and Precision Farming & Soil Mapping. These platforms combine to show a steady growth of AI integration throughout the value chain, spanning soil analysis, mechanization, planting, processing, harvesting, and finance. Not minding that the platforms are limited in number, their presence underscores rising opportunities for growth and investment. These platforms give AI-based assistance to small scale farmers, enhance productivity, minimise costs, and improve resistance to climate and market shocks. The diversity of the rising applications shows that AI in agriculture in Nigeria is at development stage but has bright future for narrowing the production gap (Samaila, 2025).

5. Analysis of Barriers to AI Scale-up in Nigerian Agribusiness

Despite the capabilities of AI technologies, their widespread adoption across Nigerian agribusiness is constrained by systemic, technological, and socio-economic barriers.

5.1 Systemic and Policy Guardrails

Absence of AI-Specific Agricultural Policies in Nigeria is manifested by lack of a formal, comprehensive legal framework governing AI implementation in agribusiness. While the National Artificial Intelligence Strategy (NAIS) provides a general outline, it lacks enforceable standards for agricultural data ownership, algorithm liabilities, and automated agronomic advice (Ebitonere, 2025; Joel et al., 2025; Choo, 2026).

Slow Institutional Integration is painfully obvious and difficult to ignore**.** Although the National Information Technology Development Agency (NITDA) oversees general IT development, integrating AI into public agricultural extension services and federal research networks remains limited (Adediran, Sakpere, and Taiwo, 2024; Haruna et al., 2026).

Poor Data Governance and Siloed Registries existence is glaring. The lack of a centralized national agricultural dataset hampers machine learning development. Datasets remain fragmented across government agencies, research institutes, and private startups, limiting developers' ability to train accurate predictive models (Oyeyemi, John, & Awodola, 2025; Samaila, 2025).

Data Privacy Concerns occupy the minds of farmers and has limiting effects because without clear national regulations regarding agronomic data privacy, their operational data could be exploited by foreign vendors or commercial aggregators without fair compensation (Oyeyemi et al., 2025; Haruna et al., 2026).

Lack of Localized Datasets as most commercial AI models are trained on European or North American datasets. Nigeria lacks comprehensive, long-term historical datasets covering localized micro-climates, indigenous crop varieties, and regional soil profiles, which reduces algorithm accuracy when deployed locally (Haruna et al., 2026; Hamisu et al., 2025).

Smallholder Land Fragmentation limits smallholder farming operations and makes systematic data collection difficult and expensive (Kumar & Doan, 2025).

Weak Extension Service Integration exists because high farmer-to-extension-agent ratios limit the reach of new innovations. Without systematic integration between AI advisory developers and public extension networks, technology adoption remains slow (Joel et al., 2025).

5.2 Technological and Infrastructural Deficits.

Rural Power Shortfalls frustrate AI systems adoption because the required electrical power is not consistent. Roughly 80% of rural Nigerians lack access to the national electricity grid (Dinrifo et al., 2022). This deficit forces AgTech startups to rely on expensive diesel generators or custom solar setups to keep remote devices operational (Joel et al., 2025; Muhammad, Usman, & Sani, 2025).

Underdeveloped Digital Infrastructure has impacted AI adoption for so long, and as at 2019, only 25.7% of the Nigerian population had access to internet services (World Economic Forum, 2020, cited in Dinrifo et al., 2022). While national initiatives expanded broadband coverage to 33% by 2019 (targeting 70% coverage), broadband access across rural farming communities remains limited (Osuagwu & Elebeke, 2019, cited in Dinrifo et al., 2022).

High Capital Hardware Costs for acquisition of advanced hardware - including IoT field probes, multispectral drones, and high-performance computing servers - requires significant upfront capital investment, presenting a financial barrier for local startups and smallholders (Sapaev et al., 2023, cited in Masasi, Ng'ombe, & Masasi, 2024).

Physical Supply Chain Bottlenecks manifest in the inability of diagnostic algorithms to address physical post-harvest losses because the cold-chain storage and transportation infrastructure remain inadequate (Zego et al., 2024; Alamu, 2025).

5.3 Socio- Economic and Cultural Barriers

High Upfront Costs and Low Margins are limiting factors because the initial expense of procuring IoT sensors, drones, and software subscriptions is often prohibitive for smallholder farmers operating on thin profit margins (Joel et al., 2025; Haruna et al., 2026). Rising input costs for seeds and fertilizers further reduce available capital for investment in technology (Kumar & Doan, 2025).

Low Profit Margins and increasing costs of increasing costs of seeds, fuel, and fertilizers frustrate small-scale and commercial farmers who end up with low profitability. This makes adoption of AI daunting in the face of limited government interventions in form of subsidies or credits (Joel, et al., 2025); (Kumar & Doan, 2025).

Digital Literacy Gaps manifest in low formal education levels among older rural farmers and presents as a barrier to using complex digital dashboards (Zhao et al., 2026). Technical analytical outputs must be simplified into actionable instructions in local languages to be effective (Otuisi, 2025).

Cultural Resistance and Misaligned Incentives are inherent limiting factors because **m**any farmers prefer traditional, ancestral farming practices and view automated advice with skepticism. Additionally, some agricultural extension agents express concern that AI tools could render their jobs obsolete (Ekperi, Owigho, & Ovwigho, 2024; Haruna et al., 2026).

Rural Insecurity and Conflict have devastating impact on farming activities as insecurity, banditry, and insurgency across parts of Northern Nigeria have disrupted farming operations, displaced rural populations, and damaged physical infrastructure, hindering technology deployment in affected regions (Otuisi, 2025).

6. The Triple-P Agric-AI Framework (Eco-AgricAI)

To address structural fragmentation in Nigerian agribusiness, standalone technical solutions are insufficient. Instead, an integrated conceptual framework that prioritises profitability, the people and planet is required - one that evaluates Economic Profitability, Environmental Resilience, and Social Inclusion as mutually reinforcing pillars (Olutumise, 2026). The proposed framework, the Triple-P **(**People**,** Planet & profit**)** Agric AI Framework for Nigeria is configured to provide a strategic guide for Tech companies as well as an appraisal system for policymakers and development partners.

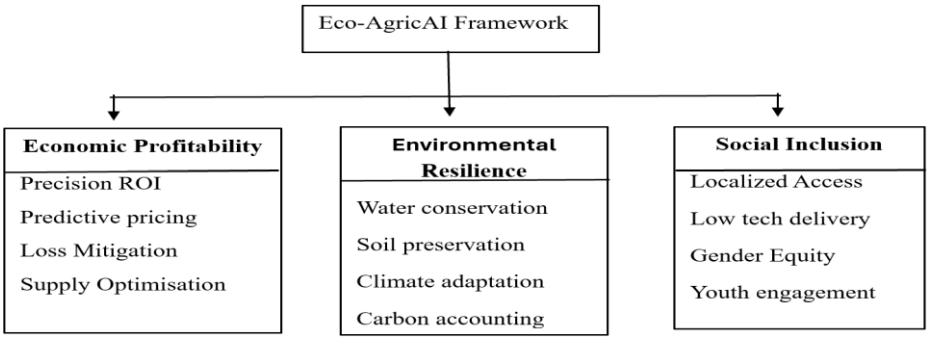


Figure 1: Triple -P Agric AI Framework
Source: Authors (2026)

6.1 Economic profitability

Economic viability requires that AI deployments improve financial performance across the agribusiness value chain. In the absence of sustainable unit economics, adoption tends to decline once donor funding phases out (Olutumise, 2026).

Return on Investment (ROI) Measurement will rank high and be beneficial if precision agriculture tools, such as drone-based canopy mapping and variable-rate applicators optimize input usage and reduce operational costs while increasing yields per hectare (Otuisi, 2025).

Predictive Pricing and Market Timing accrue as benefits as machine learning models analyze historical pricing trends, weather patterns, and market demand to help farmers make informed sales timing decisions and reduce dependence on exploitative intermediaries (Yadav et al., 2025; Singh, Dixit, & Jain, 2026).

Loss Mitigation is the result of early disease detection via computer vision that enables micro-targeted chemical applications and prevention of crop loss while minimizing chemical waste (Aliu & Sarumi, 2025; Wang & Li, 2025).

Supply Chain Optimization is achieved with AI-driven demand forecasting and dynamic vehicle routing algorithm and improves transit efficiency and help to reduce perishable crop spoilage between rural farms and urban markets (Wang, Yao, & Mao, 2026).

Closing Yield Gaps can reach 76% in developing agricultural economies. AI advisories and predictive analytics support targeted interventions that help close these production gaps (Hossain et al., 2024).

Quantifiable Yield and Profit Gains of holistic AI adoption are proven through studies that illustrate that AI adoption delivers yield increases ranging from 12% to 45% across global case studies, generating a 13% to 21% increase in net farm income (Hoque & Padhiary, 2024; Hossain et al., 2025; Olutumise, 2026). Precision agricultural practices reduce total input expenditures by up to 25% (Dinrifo et al., 2022).

Operational Efficiency is gained from deployment of autonomous equipment which reduces field overlaps and saves labour time. In high-tech greenhouse settings, AI-guided robotics have reduced labour costs by up to 40% (Hoque & Padhiary, 2024).

Agri-FinTech Access has become possible because Machine learning algorithms evaluate satellite weather data and geospatial imagery to generate alternative credit scores, enabling unbanked smallholders to access microloans and crop insurance without traditional land collateral (Dinrifo et al., 2022; Dora et al., 2022; Leung et al., 2021; Mohamed, 2023; Ruskov, 2024)

6.2 Environmental sustainability

Environmental resilience focuses on minimizing negative agricultural impacts, conserving natural resources, and supporting climate adaptation (Olutumise, 2026).

Water Conservation can be attained as AI-powered automated irrigation systems analyze real-time soil moisture and weather forecasts to apply water efficiently. These systems achieve water savings of 30% to 50% in open fields and over 60% in Closed-Environment Agriculture (CEA) systems, while cutting energy consumption by 40% (Kumar & Chandana, 2024; Aliu & Sarumi, 2025).

Soil Health and Nutrient Management can be achieved by Variable-rate nutrient applicators and soil mapping technologies which reduce nitrogen fertilizer overuse by up to 25%, significantly decreasing nitrate leaching into surrounding water bodies (Olutumise, 2026).

Predictive Climate Adaptation occurs because of ability of Machine learning models to process agro-climatic data to deliver localized early warnings for severe weather events, droughts, and pest outbreaks, allowing farmers to adjust planting schedules and seed selection proactively (Dinrifo et al., 2022; Wang & Li, 2025).

Carbon Tracking and Emissions Monitoring is achieved by AI algorithms optimizing tillage schedules, fertilizer application, and irrigation, which support soil carbon sequestration (Nie et al., 2026; Nnanguma, 2025). Additionally, field robots monitor soil emissions (such as nitrous oxide and carbon dioxide) in real time, providing data to help reduce carbon footprints (Dinrifo et al., 2022

Targeted Agrochemical Application is attainable because Computer vision-equipped smart sprayers can; distinguish weeds and pests from crops, apply agrochemicals exclusively to target areas thereby reducing chemical runoff into local ecosystems (Gruère, 2020; Partel et al., 2021; Hafeez et al., 2022; Gul & Banday, 2024).

6.3 Social Equity

Social equity evaluates how AI technologies affect rural livelihoods, gender empowerment, and resource accessibility across diverse demographics (Musa et al., 2025).

Youth Empowerment is achievable because while farm automation reduces repetitive physical labor, it creates demand for technical roles in drone operation, agri-data management, and hardware maintenance, offering skilled employment opportunities for rural youth (Olagunju, 2024).

Gender Inclusion can be attained because AI-based alternative credit scoring platforms expand financial access for female farmers who historically lacked formal land titles required as collateral for bank loans (Olutumise, 2026; Emeto et al., 2026).

Infrastructure and Accessibility to off-grid power access and rural broadband connectivity are essential for equitable digital technology adoption (John et al, 2025).

Farmer data sovereignty can be achieved if data governance frameworks prioritise farmer ownership, informed consent, and data cooperatives, ensuring smallholders retain control over their agronomic data and benefit from its commercial use (Ryan, 2022; Dara, Fard, & Kaur, 2022; Drucker et al., 2024; Wu & Zhong, 2025).
Cultural sensitivity can be respected if AI tools are co-created with farming communities, integrating voice interfaces in native languages (Hausa, Yoruba, Igbo, Pidgin) to ensure accessibility for low-literacy users (Wu & Zhong, 2025).
Democratizing Agronomic Advice through **i**mage-recognition mobile applications which allow farmers to diagnose plant diseases instantly from smartphone photos, making expert agronomic advice accessible to low-literacy producers (Dinrifo et al., 2022; Olutumise, 2026).
Mitigation of Rural Inequality Risks can be achieved when it is recognized that capital-intensive technologies are more easily adopted by larger commercial operations. So, deliberate policy support is required to ensure that low-income smallholders are not left behind due to high hardware acquisition costs (Thakur et al., 2023).
Managing Labor Restructuring is done through automated weeding, harvesting, and chemical spraying technologies which may reduce demand for manual field labor. Policy planning should account for shifting rural labor dynamics to support affected workers (Olutumise, 2026).

7. Strategic Action Pillars and Policy Recommendations

To transition AI from isolated pilots to scalable, inclusive agribusiness solutions in Nigeria, the following strategic action pillars and policy recommendations are proposed:

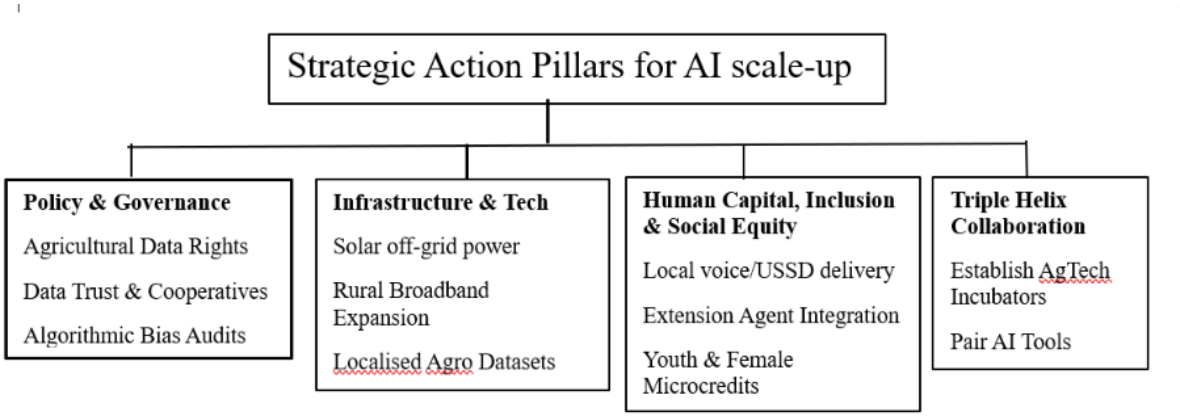


Figure 2: Strategic Action Pillars for AI Scale-up

Source: Authors (2026)

Pillar 1: Establish Regulatory Frameworks and Data Governance

Enact Agricultural Data Sovereignty Standards through which Federal agencies, led by NITDA and the Ministry of Agriculture and Food Security, should establish legal guidelines defining agricultural data ownership, privacy, and commercial rights to protect smallholders from vendors lock-in.
Institutionalize Farmer Data Trusts to support the creation of farmer-managed data trusts and cooperatives, allowing smallholders to maintain control over their aggregated data.
Mitigate Algorithmic Bias through establishment of national validation standards to ensure AI models are trained on localized micro-climates, soil types, and indigenous crop varieties rather than foreign datasets.

Pillar 2: Expand Rural Infrastructure and Off-Grid Power

Incentivize Solar-Powered Edge Devices to reverse the situation where 80% of rural communities lack grid electricity. Policy incentives and subsidies should target solar-powered edge hardware - such as solar IoT sensors and low-power processing hubs - to lower operational costs for AgTech startups.
Expand Rural Broadband Coverage since Telecom providers and government agencies can prioritize expanding broadband connectivity across agrarian belts to enable real-time farm data transmission.
Localised Agro Datasets by gathering data that provide local insights into farming systems. These data sets capture unique variations in soil health, crop yields, and other related farm data necessary for training local AI models, precision agriculture implementation, and developing food security programmes.

Pillar 3: Develop Human Capita, Inclusion and Social Equity

Deploy USSD, SMS, and Local Language Voice Platforms to address digital literacy barriers and high data costs to enable developers to scale advisory services that operate in native languages (Hausa, Yoruba, Igbo, Pidgin) via USSD, SMS, and voice systems.

Promote Equipment-Sharing Models to expand shared-economy platforms such as tractor hailing and equipment sharing to broaden access to high-cost machinery without requiring heavy upfront capital investment from smallholders.

Integrate AI into Public Extension Networks by training public agricultural extension officers to use mobile AI diagnostic tools to improve their capacity and deliver advice to local farmers.

Empower Rural Youth and Female Producers by expanding alternative credit scoring tools that utilize satellite data to provide collateral-free microloans to female farmers. In addition, establish training programs for rural youth in drone operation, data management, and equipment maintenance.

Pillar 4: Strengthen University-Industry-Government collaboration (Triple-Helix)

Establish Local AgTech Testbeds to encourage partnerships between universities, research centers (such as IITA), and private AgTech startups to field-test and validate AI tools under local farming conditions

Integrate Digital Advisory with Physical Supply Chains by pairing AI market-matching tools with investments in physical infrastructure such as solar-powered cold hubs and feeder road maintenance to convert digital efficiencies to post-harvest loss reductions.

8. Limitations and Future Research Directions

8.1 Methodological and Empirical Limitations

The review study method exhibits significant methodological and empirical constraints that limit its generalisability and analytical depth. Methodologically, the paper relies on a narrative review design utilizing thematic synthesis rather than a structured systematic protocol (e.g., PRISMA) or quantitative meta-analysis, thereby lacking formalized literature selection criteria and systematic risk-of-bias evaluations. Empirically, the research depends entirely on secondary literature and policy documents, omitting primary field data collection such as randomized controlled trials, direct surveys, or interviews with Nigerian smallholder farmers, extension agents, and developers. This reliance on secondary baselines is further compounded by a dependency on machine learning models trained on non-localized foreign datasets, national data deficits, and widespread transparency gaps regarding key financial and operational metrics across active AgTech platforms such as Kitovu, AirSmat, AgroCo, and Zenvus.

Beyond these data constraints, the study presents structural and operational limitations regarding real-world application. The proposed "Triple-P Agric AI Framework" (Eco-AgricAI) remains purely theoretical, lacking empirical field testing, longitudinal evaluation, or quantitative benchmarking within active agricultural value chains. Additionally, while the paper identifies severe systemic barriers—including an 80% rural power deficit, low broadband coverage, and active insecurity across North-Eastern and North-Western Nigeria - it fails to offer economic cost-benefit models or actionable operational roadmaps for deploying AI interventions within high-conflict or off-grid agrarian zones. Consequently, the study leaves a critical gap between high-level conceptual frameworks and practical deployment in infrastructure-deficient environments.

8.2 Future Research Opportunities

To build on this work, future academic inquiry should prioritize methodological rigor and localized empirical validation to address current gaps in Nigerian agricultural AI research. This will enable transition from narrative thematic reviews to PRISMA - guided systematic literature protocols and quantitative meta-analyses to establish robust, risk-assessed evidence on AI intervention efficacy. Concurrently, there is a critical need for primary empirical field research - utilizing randomized controlled trials (RCTs), structured surveys, and direct interviews with smallholder farmers, extension agents, and developers - to collect real-world data on technology adoption and performance. Furthermore, research must focus on building localized machine learning datasets that reflect regional soil profiles, micro-climates, and crop pest variations, supported by governance and technical frameworks to establish an interoperable national agricultural registry across Nigeria's six geopolitical zones.

Additionally, future studies must evaluate operational viability and commercial transparency within active agricultural value chains. Empirical validation and longitudinal benchmarking of theoretical models, such as the proposed Triple-P Agric AI (Eco-AgricAI) Framework, are required to test their practical effectiveness over multiple planting seasons. Research should also investigate unit economics, user retention, and financial metrics across commercial AgTech platforms (such as Kitovu, AirSmat, AgroCo, and Zenvus) to resolve widespread data transparency gaps. Finally, operational research needs to construct realistic economic cost-benefit models and low-bandwidth, edge-computing deployment roadmaps capable of functioning in off-grid or high-risk agrarian regions impacted by severe power deficits, low broadband connectivity, and local insecurity.

9. Theoretical and Practical Implications

Theoretical implications

The study helps to validate AgricAI frameworks by expanding acceptance of technology and smart agriculture models to smallholder-centric and resource-starved countries in sub-Sahara Africa. It illustrates how IoT and machine learning cycles enhance climate-resistance and conservation of natural resources. It improves the theory

on digital convergence, indicating that local AI datasets can connect data gaps between rural farmers and mass markets.

Practical Implications

The study speaks to resource optimisation attainable through smart irrigation systems and smart application of fertilizers that conserve water and minimise waste of chemicals. It also helps in early detection of risks and threats to crops through deployment of computer vision and forecasting models for identification of pest and disease in real-time. It helps to optimise logistics and minimise huge post-harvest loss through evidence-based prediction and matching buyers with sellers. It emphsises infrastructure gaps, high costs of deployment and low digital knowledge that require collective policy reforms.

10. Conclusion

While Artificial Intelligence, IoT sensors, satellite imaging, and computer vision offer tools to improve farm productivity, reduce input waste, and widen financial inclusion, technological deployment alone cannot transform the sector. Without addressing rural infrastructure deficits, digital literacy gaps, and data governance concerns, technology risks exacerbating existing inequalities (Adepoju, 2021), sustainable AI adoption may remain a mirage for a long time.

By implementing the Triple-P Agric-AI Framework, stakeholders can align Economic Profitability, Environmental Resilience, and Social Inclusion. This approach offers a structured path toward modernizing Nigerian agribusiness - ensuring that technological innovation contributes to long-term food security, environmental sustainability, and rural economic opportunity.

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