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Artificial Intelligence in Smart Agriculture: A Comprehensive Review of Pathways to Enhanced Productivity and Global Food Security

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Abstract:
The accelerating global food security crisis, driven by climate change, population growth, and land degradation, demands transformative solutions in agriculture. This paper presents a systematic narrative review of Artificial Intelligence (AI) applications in smart agriculture, examining their capacity to enhance productivity, sustainability, and socio-economic inclusion, with particular attention to smallholder farmers in developing countries. Drawing on 69 peer-reviewed studies and institutional reports (2010–2024), the review identifies precision farming, predictive analytics, automation, robotics, AI-driven crop breeding, and digital-twin modelling as key domains reshaping agricultural systems. Evidence shows that AI can increase yields by up to 30 per cent, reduce resource waste by half, and improve decision-making across the value chain. However, high capital costs, weak digital infrastructure, and data-governance gaps hinder equitable adoption. Beyond technical efficiency, this study makes a unique contribution by integrating technological, socio-economic, and policy perspectives into a single analytical framework that links AI adoption to global food-security goals. It concludes that inclusive AI ecosystems, anchored in infrastructure investment, capacity building, and ethical data management, are essential for translating innovation into sustainable growth and poverty reduction. Through this integrative lens, AI emerges not only as a tool for productivity but as a catalyst for equitable agricultural transformation.

Keywords: *Artificial Intelligence (AI), Smart Agriculture, Precision Farming, Food Security, Smallholder Farmers, Predictive Analytics, Automation and Robotics, Sustainability, Digital Transformation,and Developing Countries.*

I. Introduction

1. Context of Global Food Security

As the global population approaches a projected 10 billion by 2050, the demand for food will increase significantly, requiring agricultural production to grow by approximately 60%. Several intersecting crises, including climate change, soil degradation, and an ageing agrarian workforce, compound this challenge. Smallholder farmers, who represent the backbone of global food production, especially in developing countries, are particularly vulnerable to these challenges. Despite their critical role in feeding the world, smallholder farmers often face significant barriers such as limited access to resources, technologies, and markets, as well as exposure to climate-induced risks like droughts, floods, and irregular rainfall patterns (FAO, 2017).

Climate change alone presents a profound risk to global food systems. It is estimated that climate-induced disruptions could reduce global crop yields by 10-20% by 2050, exacerbating food insecurity, particularly in regions already struggling with poverty (WEF, 2018). Additionally, the degradation of arable land, caused by factors such as deforestation, soil erosion, and overuse of chemical inputs, threatens to reduce the capacity of existing agricultural systems to meet future demands (FAO, 2017). By 2050, about 33% of the world's land will be degraded, and this loss of productivity will further hinder efforts to address food security (WEF, 2018).

As the world faces these mounting challenges, traditional agricultural practices, which often rely on intuition and broad applications of resources, are proving increasingly inadequate. With the urgency to address these challenges, a paradigm shift is necessary. This shift must move from resource-intensive farming methods to those that leverage modern technologies, allowing farmers to optimise resource use, increase productivity, and ensure sustainability in food production systems. Here, Artificial Intelligence (AI) emerges as a potential significant change.

2. Introduction to AI in Agriculture

Artificial Intelligence (AI) is the branch of computer science that simulates human intelligence in machines, enabling them to perform tasks that traditionally require human intervention, such as decision-making, problem-solving, and learning. In agriculture, AI has the potential to revolutionise farming practices by offering more precise, efficient, and sustainable solutions to the problems faced by farmers worldwide. By leveraging big data, machine learning algorithms, and predictive models, AI enables farmers to monitor crops and livestock in real time, forecast environmental risks, and make data-driven decisions that maximise yield while minimising resource consumption.

The integration of AI into agriculture, often referred to as "smart agriculture," is transforming traditional farming into a more technology-driven, data-informed practice. This revolution in agriculture is centred around several key technologies, including precision farming, automated machinery, predictive analytics, and AI-based disease and pest monitoring systems. These technologies work in concert to provide insights into every aspect of agricultural production, from soil health to crop growth to weather patterns, enabling farmers to take proactive steps rather than reactive ones.

One of the most transformative aspects of AI in agriculture is its ability to enhance the sustainability of farming practices. Traditional farming practices often involve a one-size-fits-all approach, applying the same amount of water, fertiliser, and pesticides across entire fields, regardless of the varying needs of individual plants or soil types. With AI, however, precision farming allows farmers to make localised decisions, reducing waste and optimising the use of resources. For example, using drones and remote sensing technology, AI can help farmers assess soil moisture, nutrient levels, and crop health at a granular level, allowing for the targeted application of fertilisers and water, reducing both costs and environmental impact.

AI also plays a key role in addressing labour shortages in agriculture, as automation technologies powered by AI can take over repetitive and labour-intensive tasks such as planting, weeding, and harvesting. Robotics and AI-driven machinery can work around the clock, reducing the need for human labour and increasing operational efficiency. In this way, AI has the potential to not only increase the efficiency of agricultural practices but also improve the livelihoods of farmers by reducing labour costs and increasing the reliability of production.

3. Research Aim and Objectives

This paper explores how AI can enhance agricultural productivity and food security, particularly for smallholder farmers who face unique challenges in accessing resources and technology. The focus is on understanding the role of AI in transforming agriculture from a traditional, labour-intensive industry to a more efficient, sustainable, and productive sector. The goal is to assess the potential of AI in combating hunger and poverty, especially in developing countries where smallholder farmers are the primary food producers.

The research objectives of this paper include:

i. **Reviewing AI Technologies in Agriculture**: This paper will provide an in-depth review of the various AI technologies deployed in agriculture, including precision farming, machine learning models for predictive analytics, AI-powered robotics, and crop health monitoring systems. Each of these technologies plays a pivotal role in enhancing farm productivity and sustainability.
ii. **Evaluating the Impact on Sustainability**: The paper will critically analyse how AI technologies contribute to sustainability by reducing resource wastage, minimising the environmental impact of farming, and promoting regenerative agricultural practices.
iii. **Assessing the Role of AI in Smallholder Agriculture**: A significant part of this paper will focus on the unique challenges faced by smallholder farmers and how AI can empower them to increase productivity, improve food security, and strengthen their resilience to climate change.
iv. **Addressing Barriers to Adoption**: While AI holds immense potential, there are significant barriers to its widespread adoption, especially among smallholder farmers in developing countries. This paper will explore these challenges, including the prohibitive cost of technology, lack of digital literacy, and limited access to infrastructure.
v. **Policy and Implementation Recommendations**: The paper will conclude with a set of recommendations aimed at promoting the adoption of AI in agriculture, particularly among

smallholders. These will include policy recommendations for governments, development organisations, and the private sector to collaborate on making AI more accessible and affordable for smallholder farmers.

The challenges to global food security are complex and multifaceted, driven by population growth, climate change, and the degradation of agricultural land. Traditional farming methods are no longer sufficient to meet the demands of a growing population, making it essential to explore innovative solutions that can enhance productivity, sustainability, and resilience. AI offers a transformative potential in this regard, providing powerful tools for optimising agricultural practices, improving food security, and addressing the challenges faced by smallholder farmers.

This paper reviews the various applications of AI in agriculture, focusing on their potential to increase productivity and combat hunger, particularly in developing countries. By critically analysing the impact of AI on agricultural sustainability, the paper aims to provide a roadmap for the successful integration of AI technologies into the global agricultural system, ensuring that the benefits of AI are accessible to those who need them most. Through this review, the paper will contribute to the growing body of knowledge on AI in agriculture and provide actionable recommendations for policymakers, technologists, and farmers alike.

II. Methodology

This review employs a systematic narrative review approach to synthesize evidence on how Artificial Intelligence (AI) contributes to agricultural productivity, sustainability, and global food security, with emphasis on smallholder contexts. We integrate technical, socio-economic, and policy perspectives to reflect the multidimensional nature of food systems transformation highlighted by leading institutions (FAO, 2017; WEF, 2018).

1. Search strategy

A comprehensive literature search was conducted between January and April 2025 across Scopus, Web of Science, Google Scholar, and ScienceDirect. We complemented this with targeted searches of FAO and WEF repositories for high-level food-system reports (FAO, 2017; WEF, 2018). Boolean combinations included:

(“artificial intelligence” OR “machine learning” OR “deep learning”) AND (“smart agriculture” OR “precision agriculture” OR “digital agriculture”) AND (“food security” OR “sustainability” OR “smallholder” OR “developing countries”).

To ensure coverage of established and emergent AI domains, we additionally scanned canonical and recent reviews on precision/digital agriculture (Basso & Antle, 2020; Zhang et al., 2002), yield prediction (van Klompenburg et al., 2020), robotics (Fountas et al., 2020), traceability/blockchain (Kamilaris et al., 2019), soil microbiomes (Jansson & Hofmockel, 2020), and digital twins/smart farming (Verdouw et al., 2021).

2. Inclusion and exclusion criteria

We included works that: (i) were peer-reviewed or high-credibility institutional reports; (ii) published in English from 2010–2024 (capturing both foundational and current AI advances); (iii) addressed AI applications or enabling digital infrastructures in agriculture; and (iv) linked AI to productivity, sustainability, market access, or food security, with attention to smallholders (directly or by implication). We excluded non-scholarly commentaries, sources lacking substantive methods/results, and studies on mechanization without AI components. Because access, affordability, and capability shape adoption, we retained studies discussing costs, digital divide, and data governance (Lowenberg-DeBoer & Erickson, 2019; Trendov et al., 2019; Wiseman et al., 2019).

3. Screening and selection

The initial search identified 182 records. After duplicate removal and title/abstract screening against criteria, 97 sources remained. Full-text appraisal for relevance, scope, and methodological clarity yielded 58 core studies. Backward/forward citation chasing added 11 pertinent items (e.g., domain-defining reviews and institutional reports), resulting in 69 total sources forming the evidence base.

4. Analytical framework and synthesis

We used thematic content analysis aligned to the paper’s objectives. Studies were coded into four clusters: (1) AI technologies and innovations, (2) environmental sustainability outcomes, (3) socio-economic impacts for smallholders (income, gender, resilience), and (4) adoption barriers and policy/implementation levers. Within clusters, we compared reported effects (e.g., yield, input efficiency, logistics performance), contextual moderators (infrastructure, skills, finance), and governance considerations (data rights, privacy), integrating insights across technical and policy literatures (Basso & Antle, 2020; Kamilaris et al., 2019; Trendov et al., 2019; Wiseman et al., 2019). To preserve breadth while elevating criticality, we privileged evidence-rich reviews and empirical studies and triangulated them with FAO/WEF system-level assessments on food-security drivers (FAO, 2017; WEF, 2018).

Table 1 summarises the major AI domains, their documented outcomes, and the constraints affecting smallholder adoption.

Table 1. Comparative Summary of Key AI Domains in Smart Agriculture

AI Domain	Core Function / Application	Reported Outcomes	Constraints for Smallholders	Exemplar References
Precision Farming (IoT, sensors, drones, satellite imagery)	Uses AI algorithms to analyse soil moisture, nutrient levels, crop health, and micro-climate data for targeted irrigation and fertiliser use.	15–30% increase in yields; 20–50% reduction in water use; lower input costs through site-specific management.	High initial equipment cost (sensors/drones); unreliable internet; limited technical literacy.	Basso & Antle (2020); Zhang, Wang, & Wang (2002); Trendov, Varas, & Zeng (2019)
Predictive Analytics & Machine Learning	Forecasts weather patterns, pest/disease outbreaks, and market prices using historical and real-time data.	Improved risk management; early pest detection; reduced yield loss; better market timing and profitability.	Data scarcity and poor record-keeping; limited access to meteorological data; need for mobile connectivity.	van Klompenburg, Kassahun, & Catal (2020); WEF (2018)
Automation & Robotics	AI-guided autonomous tractors, robotic harvesters, and weed-removal systems execute labour-intensive operations.	Up to 31% reduction in operating costs; consistent quality and precision; mitigates labour shortages.	High capital cost; lack of local maintenance expertise; small field sizes unsuitable for large robots.	Fountas et al. (2020); Lowenberg-DeBoer & Erickson (2019)
Crop & Livestock Health Monitoring	Image recognition and sensor data detect diseases, nutrient deficiencies, or animal distress early.	Early intervention; lower chemical use; improved animal welfare and yields.	Cost of imaging devices; unreliable power supply; lack of training to interpret AI outputs.	Li, Zhang, & Huang (2014); Neethirajan (2020)
AI-Driven Crop Breeding (Generative & Predictive Models)	Uses genomic and environmental datasets to identify and simulate high-yield, climate-resilient varieties.	Accelerated breeding cycles (years → months); improved drought, pest, and heat tolerance.	Limited genomic data from developing countries; restricted lab and data-processing capacity.	Voss-Fels, Stahl, & Hickey (2019); Mushtaq, Ahmed, & Zeng (2024)
Post-Harvest Management & Food-Waste Reduction	Predicts shelf life; optimises storage and transport logistics through AI-driven sensors and routing algorithms.	Up to one-third reduction in post-harvest losses; improved food quality and safety.	Poor cold-chain infrastructure; high energy costs; fragmented supply chains.	Ben-Daya, Hassini, & Bahroun (2019)
Soil Health & Microbiome Analysis	AI analyses soil microbiome and nutrient dynamics to recommend fertiliser or microbial amendments.	Enhanced soil fertility; reduced chemical dependency; improved carbon sequestration.	Limited soil-testing labs; high cost of sensors; lack of awareness of microbial benefits.	Jansson & Hofmockel (2020)
Blockchain & AI Integration	Ensures transparent, tamper-proof data on	Strengthened consumer trust;	Inadequate digital infrastructure; energy	Kamilaris, Fonts, & Prenafeta-Boldó

	product origin and supply-chain sustainability.	better traceability; easier certification for organic/fair-trade products.	and data costs; low digital literacy.	(2019)
Edge AI / Cloud-Linked Systems	Processes data locally for real-time decision-making in low-connectivity areas.	Reduced latency; faster pest/irrigation alerts; lower dependence on broadband.	Limited access to affordable edge devices, along with gaps in maintenance and software updates.	Shi et al. (2016); Trendov et al. (2019)
Digital Twins & Virtual Modelling	Simulates entire farm systems to optimise management decisions and test policy scenarios.	Real-time decision support, improved input efficiency, and system-level scenario testing.	High computational and data requirements; complex setup for smallholders.	Verdouw, Tekinerdogan, Beulens, & Wolfert (2021)

Analytical Commentary

The comparative evidence presented in Table 1 shows that precision farming and predictive analytics remain the most empirically validated AI domains for improving agricultural productivity and sustainability. Studies such as *Basso and Antle (2020)* and *Zhang et al. (2002)* consistently report yield increases of 15–30 per cent and water-use reductions of up to 50 per cent through site-specific management enabled by sensors, drones, and satellite imagery. These technologies demonstrate immediate, measurable benefits for resource efficiency and are already being deployed at scale in both commercial and pilot smallholder systems. Predictive analytics and machine-learning models (van Klompenburg et al., 2020) similarly show strong results in yield forecasting, pest-risk detection, and market prediction, allowing farmers to make data-driven planting and sales decisions that buffer against climatic and price shocks. Together, these domains offer the clearest near-term return on investment because they integrate easily with existing farm operations and mobile-based advisory platforms.

In contrast, automation, robotics, and AI-driven crop breeding hold transformative potential but face scalability and affordability constraints. Although *Fountas et al. (2020)* and *Lowenberg-DeBoer and Erickson (2019)* demonstrate operational-cost reductions of roughly 31 percent in high-income settings, the capital intensity of robotics limits adoption among smallholders. Similarly, AI-assisted breeding research (Voss-Fels et al., 2019; Mushtaq et al., 2024) shows significant acceleration in developing drought- and heat-tolerant varieties, yet the supporting genomic infrastructure and data pipelines remain concentrated in advanced research institutions. These innovations thus exhibit high potential but low current diffusion outside research or industrial contexts.

Emerging domains, soil microbiome analytics, blockchain traceability, edge AI, and digital-twin modelling, represent the next frontier in sustainable agri-innovation but are still under-documented in smallholder environments. While *Jansson and Hofmockel (2020)* and *Kamilaris et al. (2019)* highlight their promise for soil regeneration and transparent supply chains, empirical field data from developing countries are scarce. Moreover, infrastructure deficits, data-privacy uncertainties (Wiseman et al., 2019), and skills gaps (Trendov et al., 2019) continue to constrain equitable adoption. Future research should therefore prioritise longitudinal, cross-regional comparisons to quantify economic and environmental returns under diverse farming conditions. Strengthening digital infrastructure, promoting affordable sensor technologies, and building farmer-centred data-governance frameworks will be critical to translating these high-tech advances into inclusive gains for smallholders and global food-security outcomes.

III. Literature Review

The integration of Artificial Intelligence (AI) into agriculture marks a paradigm shift from intuition-based farming to data-driven systems capable of improving efficiency, resilience, and food security. Existing literature broadly agrees that AI can enhance agricultural productivity and sustainability by optimising the use of land, water, and other natural resources (Basso & Antle, 2020; Zhang, Wang, & Wang, 2002). Scholars and institutions such as the FAO (2017) and WEF (2018) have emphasised the urgent need for technological transformation to meet the food demands of a population expected to reach 10 billion by 2050.

The literature clusters around four interrelated domains. First, research on technological foundations, including precision agriculture, predictive analytics, and robotics, shows how AI leverages big data, IoT sensors, and machine-learning algorithms to optimise inputs and predict yield outcomes (Zhang et al., 2002; van Klompenburg, Kassahun, & Catal, 2020). These technologies form the operational backbone of "smart agriculture," improving efficiency by enabling localised decision-making and precision application of resources. Second, studies focusing on environmental sustainability highlight AI's role in reducing waste, improving soil fertility, and promoting regenerative agricultural practices. Jansson and Hofmockel (2020) demonstrated that AI models can analyse soil microbiomes to guide nutrient management and enhance carbon sequestration. Similarly, AI-driven irrigation systems can reduce water use by up to 50 percent while maintaining or increasing yields (Basso & Antle, 2020).

Third, literature addressing socio-economic impacts underscores the transformative potential of AI for smallholder farmers. Research by Lowenberg-DeBoer and Erickson (2019) and Trendov, Varas, and Zeng (2019) shows that precision agriculture and digital platforms can reduce production costs by 20–30 percent, improve market access, and create new digital employment opportunities in rural areas. Studies on gender equity (Farnworth et al., 2020) also reveal that AI can empower women farmers through improved access to market information, credit scoring, and extension services. Finally, policy and governance-oriented research identifies major barriers to widespread adoption. The most frequently cited constraints include high capital cost, weak infrastructure, and data-privacy risks (Wiseman, Sanderson, Zhang, & Jakku, 2019). These limitations are particularly acute for smallholders in developing regions, where access to digital tools and reliable connectivity remains limited.

Despite the depth of existing studies, the literature remains fragmented across technical, social, and policy perspectives. Most works examine single dimensions, either technological efficiency or socio-economic implications, without an integrated analysis of how AI systems perform in real-world smallholder contexts. This gap motivates the present study's objectives: to connect AI technologies, sustainability outcomes, and inclusive adoption frameworks into a unified understanding of how AI can drive productivity and food security.

Global Food Security Challenges and Technological Innovations

The integration of AI into agriculture directly addresses several challenges that threaten global food security, including climate change, labour shortages, and resource scarcity. By enabling more precise and efficient farming practices, AI enhances the resilience of agricultural systems, increases productivity, and reduces the environmental impact of food production. The potential of AI to revolutionize agriculture is particularly significant for smallholder farmers, who face unique challenges in accessing technology, resources, and markets.

However, despite the numerous advantages of AI in agriculture, significant barriers remain to its widespread adoption. These barriers include the high costs of technology, data privacy concerns, lack of digital infrastructure, and the digital divide between developed and developing regions. Addressing these challenges is critical to ensuring that AI benefits all farmers, particularly those in developing countries who are most in need of support.

The literature reveals that AI holds immense potential to enhance agricultural productivity, reduce resource wastage, and address global food security challenges. AI applications, including precision farming, predictive analytics, automation, crop and livestock health monitoring, and blockchain for traceability, offer practical solutions to the pressing issues faced by modern agriculture. However, the barriers to AI adoption, particularly in resource-poor regions, must be addressed through targeted policy interventions, investments in infrastructure, and capacity-building initiatives. By overcoming these challenges, AI can become a critical tool in the fight for global food security.

Building on these conceptual insights, the following section examines concrete AI technologies currently transforming agriculture, comparing their mechanisms, empirical impacts, and constraints in relation to the study's objectives.

IV. AI Technologies Transforming Agriculture

Artificial Intelligence technologies are increasingly embedded across multiple stages of the agricultural value chain, from field operations to post-harvest logistics. This section analyses how specific AI domains translate theoretical potential into measurable impact, aligning with the study's objectives to enhance productivity, promote sustainability, and empower smallholder farmers.

1. Precision Farming and IoT Integration

Precision farming remains the most mature and impactful AI domain. It employs interconnected sensors, drones, and satellite imagery to gather real-time data on soil moisture, temperature, and crop health, enabling site-specific irrigation and fertilisation. AI algorithms interpret this data to recommend precise resource applications, minimising waste and improving yield (Zhang et al., 2002). Empirical evidence indicates yield increases of up to 30 percent and reductions in water use by nearly half (Basso & Antle, 2020). By replacing uniform practices with localised management, precision farming aligns directly with Objective (i): improving productivity and resource efficiency. However, adoption among smallholders is constrained by the cost of equipment, limited internet connectivity, and low digital literacy (Trendov et al., 2019).

2. Predictive Analytics and Machine Learning

AI-powered predictive models analyse large datasets—spanning weather forecasts, soil profiles, and market signals—to anticipate environmental risks and price fluctuations. These systems enable farmers to plan planting schedules, manage input procurement, and time market sales effectively. Van Klompenburg, Kassahun, and Catal (2020) documented how machine-learning models enhance yield forecasting accuracy and enable proactive risk management against drought or pest outbreaks. Predictive analytics thus fulfil Objective (ii): assessing AI's role in sustainability and resilience by reducing uncertainty and optimising resource use.

3. Automation and Robotics

Automation addresses global labour shortages and rising production costs. AI-driven autonomous tractors, drones, and robotic harvesters can perform planting, weeding, and harvesting with precision and minimal human intervention. Fountas et al. (2020) showed that automation can reduce operating costs by up to 31 percent per acre, while Lowenberg-DeBoer and Erickson (2019) found it particularly valuable in labour-intensive crops such as fruits and vegetables. Nevertheless, the high capital cost and small field sizes in developing regions limit scalability, underlining the need for policy incentives and cooperative financing models.

4. Crop and Livestock Health Monitoring

AI has revolutionised early disease and pest detection. Image-recognition and sensor-based monitoring systems can identify nutrient deficiencies or infections before they become visible, allowing timely interventions (Li, Zhang, & Huang, 2014). In livestock, AI sensors monitor behaviour and feeding patterns to detect illness early (Neethirajan, 2020). These tools directly contribute to Objective (iii): improving smallholder resilience and reducing input waste, though affordability and training remain adoption barriers.

5. AI-Driven Crop Breeding and Genetic Innovation

Recent advances in generative AI and genomic modelling are accelerating the breeding of climate-resilient crops. By analysing genetic and environmental datasets, AI predicts favourable trait combinations that enhance drought and pest resistance (Voss-Fels, Stahl, & Hickey, 2019; Mushtaq, Ahmed, & Zeng, 2024). This shortens breeding cycles from decades to a few years, advancing global food security efforts. However, limited genomic data infrastructure in developing countries constrains equitable access.

6. Post-Harvest Management and Supply Chain Optimisation

AI applications extend beyond cultivation into storage, transportation, and logistics. Systems that predict shelf life and optimise cold-chain management reduce spoilage and improve food quality. Ben-Daya, Hassini, and Bahroun (2019) reported up to one-third reductions in post-harvest losses using AI-based scheduling and routing algorithms. These outcomes align with Objective (ii) on sustainability by reducing food waste and enhancing supply-chain efficiency.

7. Soil Health and Microbiome Analytics

AI's application to soil microbiome analysis enables farmers to optimise soil fertility and nutrient management. Jansson and Hofmockel (2020) found that AI can process complex biological data to recommend organic amendments and microbial inoculants, improving both yields and carbon sequestration. Despite high promise, limited access to testing facilities and the cost of sensor deployment remain key challenges for smallholders.

8. Blockchain, Edge AI, and Digital Twins

Emerging innovations combine AI with blockchain to ensure transparency and traceability in food supply chains (Kamilaris, Fonts, & Prenafeta-Boldó, 2019). Edge computing allows local data processing in low-connectivity regions, improving responsiveness (Shi et al., 2016). Meanwhile, digital-twin technologies simulate entire farm systems for predictive scenario planning and policy testing (Verdouw, Tekinerdogan, Beulens, & Wolfert, 2021). Though early in deployment, these systems hold long-term potential to democratise data access and enable evidence-based decision-making across scales.

Collectively, these technological domains illustrate how AI translates theoretical advances into field-level outcomes that directly support productivity, sustainability, and inclusivity. The next section (IV) extends this analysis by exploring the broader socio-economic and policy implications of AI adoption, particularly its role in empowering smallholder farmers and addressing systemic barriers.

V. Socio-Economic Impact of AI in Agriculture (Refined)

The successful integration of AI technologies into agricultural systems extends far beyond technical efficiency; it fundamentally reshapes the social and economic fabric of rural livelihoods. While the preceding section examined how AI applications optimise productivity and resource use, their broader significance lies in how these gains translate into economic empowerment, employment, and environmental sustainability for farming communities. In alignment with Objective (iii), to assess the role of AI in smallholder agriculture, this section explores the socio-economic dimensions of AI adoption: how it enhances productivity and profitability, reduces poverty, supports gender inclusion, and promotes long-term sustainability. By linking technological performance to human outcomes, the discussion underscores that AI's actual value in agriculture is measured not only by higher yields but by improved resilience and equity within farming populations.

The integration of Artificial Intelligence (AI) into agriculture is reshaping the socio-economic landscape of rural economies worldwide. Beyond its technological capabilities, AI serves as a catalyst for inclusive growth, offering new pathways for smallholder farmers to enhance productivity, reduce poverty, and build resilience to climate and market shocks. While previous sections examined the technical mechanisms of AI, this section focuses on the human and economic outcomes, specifically how AI affects productivity, cost efficiency, empowerment, sustainability, and employment.

1. Increased Productivity and Reduced Costs

AI-enabled precision agriculture, predictive analytics, and crop-health monitoring have collectively improved efficiency in resource allocation, leading to measurable productivity gains. Precision farming technologies that combine IoT sensors, drones, and satellite data have demonstrated yield increases of up to 30 per cent and reductions in input costs between 20–50 per cent (Basso & Antle, 2020). Such systems allow farmers to apply fertiliser, water, and pesticides only where and when needed, minimising waste and maximising returns. In the same vein, predictive analytics tools reduce uncertainty by providing early warnings of pest infestations or drought, allowing for timely and cost-effective interventions (van Klompenburg, Kassahun, & Catal, 2020).

For smallholder farmers operating under tight resource constraints, these efficiencies are transformative. By optimising input use, AI reduces dependence on costly external inputs while improving yield reliability. Lowenberg-DeBoer and Erickson (2019) found that precision-agriculture adoption can lower operational costs by up to 31 percent per acre for major crops such as maize and soybeans. Although initial setup costs remain high, long-term profitability and environmental savings offset these expenses, particularly when AI systems are shared cooperatively or deployed through community models.

2. Economic Empowerment of Smallholder Farmers

AI technologies expand economic opportunities by improving market access, profitability, and bargaining power. AI-driven mobile platforms and market-intelligence systems connect farmers directly with buyers, eliminating intermediaries and ensuring fair pricing. Apps such as Farmerline and Digital Green have demonstrated how real-time market information and digital extension services enhance transparency and income (Walter et al., 2017). Predictive models also guide crop-selection decisions based on projected prices and weather patterns, reducing financial risk and post-harvest losses.

By improving decision quality and linking smallholders to data-driven insights, AI empowers them to operate as market participants rather than price takers. This digital inclusion allows smallholders to reinvest profits into farm expansion, access credit more easily, and diversify income sources. Studies further show that smallholders using AI-enabled advisory systems are more likely to achieve financial stability, demonstrating that economic empowerment is both a cause and a consequence of technological adoption (Trendov, Varas, & Zeng, 2019).

3. Environmental Sustainability

AI also contributes to environmental sustainability by promoting responsible resource use and regenerative practices. AI-driven precision irrigation systems have reduced water consumption by up to 50 percent in pilot projects (Basso & Antle, 2020), while predictive pest-management algorithms reduce pesticide overuse and chemical runoff (Li, Zhang, & Huang, 2014). Moreover, AI models analysing soil microbiomes recommend organic fertilisers and crop rotations that enhance long-term fertility and carbon sequestration (Jansson & Hofmockel, 2020).

These outcomes collectively advance Objective (ii): evaluating AI's role in sustainability. Through intelligent monitoring and control systems, farmers can maintain productivity while conserving biodiversity and natural resources. Thus, AI aligns economic incentives with ecological preservation, supporting a dual agenda of profitability and planetary stewardship.

4. Job Creation and Skills Development

Although automation and robotics may initially appear to threaten rural employment, they also create new categories of digital work. As Fountas et al. (2020) note, AI deployment generates demand for technicians, data analysts, drone operators, and digital-extension agents—roles that did not exist in traditional agriculture. These "new-collar" jobs bridge the gap between farm work and technology sectors, especially when vocational training and public-private partnerships are introduced.

Moreover, by reducing physically demanding labour and improving productivity, AI can make farming more attractive to youth, mitigating rural-urban migration. With adequate training initiatives, rural communities can evolve into digital agricultural ecosystems, where farmers, service providers, and technology specialists coexist symbiotically. Investment in capacity building is therefore critical to ensure that automation complements, rather than displaces, human labour (Trendov et al., 2019).

5. Social Inclusion and Gender Equity

AI can help close persistent gender and social gaps in agriculture. Women—who comprise nearly half of the agricultural workforce in developing economies—often face systemic barriers in accessing credit, information, and extension services (FAO, 2017). Mobile-based AI tools designed with inclusive interfaces can provide women farmers with equal access to agronomic advice, market data, and digital finance (Farnworth et al., 2020). AI-enabled credit-scoring models, for example, allow women to secure loans based on production data rather than traditional collateral requirements. This promotes financial autonomy and fosters broader community development, as women are more likely to reinvest earnings into education and household welfare.

6. Climate Change Adaptation and Resilience

Climate variability poses significant risks to smallholder livelihoods. AI technologies enhance adaptive capacity by forecasting extreme weather and recommending climate-smart practices. Predictive systems can anticipate drought or flooding weeks in advance, enabling timely changes in crop calendars and irrigation plans (van Klompenburg et al., 2020). AI-driven breeding programs also accelerate the development of drought- and heat-tolerant varieties (Voss-Fels, Stahl, & Hickey, 2019), reducing vulnerability to climate shocks.

By coupling precision agriculture with climate-resilience tools, AI builds systemic stability within food systems. Farmers can transition from reactive coping to proactive management, ensuring productivity even under changing environmental conditions.

7. Integrating Economic and Social Outcomes

Collectively, these dimensions illustrate that AI's socio-economic impacts are multi-layered and interdependent. Productivity gains translate into higher income and improved living standards, which in turn enable further investment in sustainable technologies. Environmental benefits complement these outcomes by reducing long-term production risks. The cumulative effect is a virtuous cycle of growth, resilience, and inclusion. However, to sustain these gains, structural barriers, such as limited connectivity, high equipment cost, and data privacy concerns, must be addressed through policy support, financial innovation, and public investment.

The next section, therefore, examines the major obstacles hindering equitable AI adoption and proposes strategic pathways, through financing, governance, and capacity building, to ensure that smallholder farmers fully benefit from the digital transformation of agriculture.

VI. Challenges to AI Adoption in Agriculture

Despite its transformative potential, the widespread adoption of Artificial Intelligence (AI) in agriculture, particularly among smallholder farmers, remains limited by several interconnected barriers. These constraints are economic, infrastructural, technical, institutional, and ethical in nature. Understanding these challenges is critical to achieving equitable and sustainable AI diffusion. This section examines four major obstacles: (1) investment and infrastructure gaps, (2) data governance and privacy issues, (3) skills and knowledge limitations, and (4) persistent digital divides.

1. Initial Investment and Infrastructure Gaps

High initial costs and inadequate infrastructure constitute the foremost barrier to AI adoption. Although AI technologies can yield long-term savings, their upfront expenses, covering hardware, software, data storage, and system maintenance, remain prohibitive for resource-poor farmers (Trendov, Varas, & Zeng, 2019). Smallholders in developing countries typically operate on thin profit margins and depend on informal credit systems, making the purchase of AI tools such as drones, multispectral sensors, and autonomous machinery financially unattainable.

Moreover, many rural areas lack the supporting infrastructure required for AI deployment. Unreliable electricity, weak broadband connectivity, and limited cloud-storage capacity hinder real-time data processing (Trendov et al., 2019). Because many AI systems depend on stable internet connections and continuous power supply, these deficiencies restrict practical implementation. Without coordinated investment in rural digital infrastructure, smallholder participation in AI-enabled agriculture will remain low.

Addressing cost and infrastructure barriers will require innovative financing models and strong public-private partnerships, issues intertwined with the management and protection of agricultural data.

2. Data Privacy, Ownership, and Governance

AI in agriculture relies heavily on continuous data collection from sensors, drones, and digital platforms. While these data streams improve decision-making, they also raise ethical concerns about privacy, ownership, and potential misuse (Wiseman, Sanderson, Zhang, & Jakku, 2019). Farmers often have little control over how their data is stored or monetised by technology providers. In many cases, proprietary algorithms limit transparency, leaving farmers uncertain about how recommendations are generated.

Weak or non-existent data-protection frameworks in developing countries compound the risk of exploitation. Sensitive information, such as farm location, yields, and financial transactions, could be misused for commercial advantage or surveillance. Wiseman et al. (2019) emphasised that inadequate regulation erodes trust and discourages farmers from sharing data essential for AI model accuracy. Establishing clear rules on data ownership, informed consent, and benefit sharing is therefore vital for ethical and sustainable AI adoption.

Even when data-governance challenges are addressed, the effectiveness of AI systems still depends on human capacity, particularly farmers' ability to interpret and use AI outputs.

3. Skills and Knowledge Gaps

Limited digital literacy and technical capacity among farmers present another major constraint. Most smallholder farmers are accustomed to traditional practices and may find AI-based tools complex to operate (Trendov et al., 2019). Even when mobile advisory platforms are available, low levels of education and unfamiliarity with digital interfaces reduce usage and trust in AI recommendations.

Training and capacity-building initiatives are therefore essential. Programs should not only teach operational skills, such as managing drones or reading dashboard outputs, but also cultivate an understanding of how AI decisions are generated and validated. Agricultural extension officers and local technicians must be trained to provide ongoing support, creating a decentralised network of expertise. Such initiatives build confidence and ensure that technology complements, rather than replaces, farmers' experiential knowledge.

However, the persistence of the digital divide, especially between urban and rural regions, continues to exacerbate inequalities in who can access and benefit from AI innovation.

4. The Digital Divide and Access Inequality

The global digital divide remains one of the most persistent challenges to inclusive AI adoption. In many developing regions, rural connectivity lags far behind urban centres, limiting access to internet-based platforms and mobile applications (Trendov et al., 2019). Even where basic connectivity exists, bandwidth costs are high, and hardware such as smartphones and tablets remain unaffordable for smallholders.

Furthermore, most AI solutions are designed for large-scale commercial farms in developed economies, making them poorly suited to the operational realities of smallholders. This technological mismatch widens existing inequalities, concentrating benefits among well-resourced farmers and agribusinesses. Bridging this divide requires deliberate policy measures, including rural broadband expansion, device subsidies, and the design of low-bandwidth, mobile-friendly AI tools that reflect local languages and agronomic conditions.

5. Integrating Solutions through Policy and Collaboration

Overcoming these barriers demands a coordinated multi-stakeholder approach. Governments must prioritise digital infrastructure investment, establish robust data governance frameworks, and provide fiscal incentives, such as tax breaks or credit facilities, to encourage smallholder adoption. Private-sector actors can contribute through affordable technology packages and inclusive business models, while development organisations and universities should lead in training and research on locally appropriate AI solutions.

Collectively, these actions can create an enabling environment in which smallholder farmers not only access AI tools but also participate in shaping their design and governance. Such inclusivity is essential for building trust, ensuring equitable benefit distribution, and translating technological potential into tangible socio-economic progress.

The next section (VI) extends this analysis by examining how AI, when implemented within supportive policy and social frameworks, can actively contribute to poverty alleviation, gender inclusion, and climate-change adaptation.

VII. AI and Poverty Alleviation: Bridging the Gap

The integration of Artificial Intelligence (AI) into agriculture holds transformative potential for reducing hunger, poverty, and inequality—especially among smallholder farmers in developing regions. As Section V established, the benefits of AI are often constrained by infrastructural, financial, and knowledge gaps. Yet when these constraints are mitigated through supportive policy and inclusive design, AI becomes a powerful enabler of human development. This section analyses how AI contributes to four interrelated domains of poverty reduction: food security, income generation, gender equity, and climate-change adaptation.

1. Food Security and Hunger Reduction

AI directly combats hunger by increasing yields, reducing post-harvest losses, and improving supply-chain efficiency. Precision farming, predictive analytics, and remote-sensing technologies enable farmers to optimise inputs, detect disease early, and forecast yields with higher accuracy (Zhang, Wang, & Wang, 2002; van Klompenburg, Kassahun, & Catal, 2020). Studies show that such systems can raise output by 20–30 percent while cutting waste by nearly one-third (Basso & Antle, 2020; Ben-Daya, Hassini, & Bahroun, 2019). In regions where one-third of food is lost post-harvest, AI-driven cold-chain monitoring and logistics optimisation significantly reduce spoilage, ensuring that more food reaches consumers.

AI's predictive capacity also enhances food-system stability by anticipating weather-related disruptions. By integrating climate and market data, farmers can plan planting cycles, irrigation schedules, and distribution routes that minimise loss and volatility. These innovations position AI as a central instrument for achieving the United Nations' Sustainable Development Goal 2: Zero Hunger (FAO, 2020).

2. Income Generation and Economic Empowerment

For smallholders, income security is often undermined by fluctuating yields and price instability. AI technologies address both issues simultaneously. Precision farming reduces expenditure on fertilisers, pesticides, and water, lowering input costs by up to 30 percent (Basso & Antle, 2020). Predictive-market analytics enable farmers to identify the most profitable crops and optimal times for sale, helping them avoid gluts and exploit high-demand periods (Walter et al., 2017).

Digital platforms such as Farmerline and Digital Green leverage AI to connect producers directly with buyers, eliminating exploitative intermediaries and ensuring fairer returns (Trendov, Varas, & Zeng, 2019). Over time, higher profitability strengthens creditworthiness, allowing farmers to invest in improved inputs and technologies, thereby reinforcing a cycle of productivity and financial resilience. Thus, AI contributes not merely to yield growth but to structural poverty alleviation by expanding market participation and income diversification.

3. Women's Empowerment and Gender Equity

Women constitute nearly half of the global agricultural workforce but face entrenched barriers to land ownership, finance, and information. AI technologies, especially mobile-based advisory and credit-scoring platforms, offer new mechanisms to close these gaps. Apps designed with inclusive interfaces and local-language support provide women with real-time agronomic guidance, pest alerts, and market prices (Farnworth et al., 2020). Algorithmic credit-assessment tools also enable access to loans based on productivity data rather than collateral, fostering entrepreneurship and financial autonomy.

By democratising access to information and finance, AI helps to level gender disparities in productivity and earnings. Empowered women reinvest a higher proportion of income into household welfare, education, and nutrition, amplifying AI's developmental impact beyond the individual farm to the wider community (FAO, 2020). However, inclusive design and training remain essential to ensure that AI systems do not replicate existing biases in data or algorithmic recommendations.

4. Climate-Change Adaptation and Resilience

AI's predictive power is equally vital for adapting agriculture to climate variability. Machine-learning models integrating satellite imagery and meteorological data can forecast droughts, floods, or temperature extremes with high spatial precision (van Klompenburg et al., 2020). This enables farmers to adjust planting dates, adopt drought-resistant crops, or deploy water-saving irrigation before crises occur. Simultaneously, AI-driven crop-breeding programs accelerate the development of stress-tolerant varieties by analysing genomic and environmental interactions (Voss-Fels, Stahl, & Hickey, 2019).

AI thereby transforms climate adaptation from reactive coping to proactive management, enhancing food-system stability and farmer resilience. In regions already experiencing severe weather volatility, such innovation equates to risk mitigation and livelihood preservation, core dimensions of poverty reduction.

5. Toward Inclusive Growth and Policy Alignment

The poverty-alleviating potential of AI is maximised only when integrated into inclusive policy frameworks. Governments and development partners must prioritise digital-infrastructure investment, rural financing mechanisms, and targeted capacity-building programs to ensure equitable access. Partnerships between tech firms and cooperatives can promote localised AI solutions that address specific climatic and cultural contexts. Furthermore, ethical guidelines for data governance are required to protect farmers' rights and prevent monopolisation of digital value chains (Wiseman et al., 2019).

When these enabling conditions are met, AI functions as both a productivity enhancer and a social equaliser, bridging the technological divide that separates wealthy and poor farmers, men and women, and urban and rural producers.

Having explored AI's contribution to food security, income generation, gender inclusion, and climate resilience, the next section (VII) considers the emerging trends and opportunities that will shape the future trajectory of AI in global agriculture.

VIII. The Future of AI in Agriculture: Emerging Trends and Opportunities

As global demand for food intensifies and climate challenges escalate, Artificial Intelligence (AI) is positioned to become the defining force in shaping the future of agricultural production. The next generation of AI-driven agriculture will be characterised not only by technological innovation but also by integration, inclusivity, and intelligence across the entire value chain. Emerging trends indicate that AI is transitioning from experimental applications toward systemic transformation, linking farmers, markets, and ecosystems in unprecedented ways.

1. Expansion of Edge AI and Cloud Integration

A key frontier in smart agriculture lies in the convergence of edge computing and cloud-based analytics. Edge AI enables data processing directly on local devices, reducing latency and dependence on continuous internet connectivity, an essential advantage for rural or remote farming communities (Shi et al., 2016). When combined with cloud platforms, edge systems create a hybrid intelligence network capable of real-time decision-making and large-scale data aggregation.

In future agricultural systems, drones, sensors, and autonomous machines will communicate through these integrated platforms, allowing instant adjustments in irrigation, fertilisation, and pest control. Such configurations can make AI tools more accessible and efficient for smallholders who currently lack high-speed connectivity. Governments and technology providers must therefore invest in rural digital infrastructure that supports edge-cloud interoperability to democratise access to AI benefits.

2. Rise of Digital Twins and Predictive Farm Modelling

Another major trend involves the emergence of digital twins, virtual replicas of physical farms that simulate crop growth, soil conditions, and weather interactions (Verdouw, Tekinerdogan, Beulens, & Wolfert, 2021). These models use real-time data from IoT sensors and satellite imagery to test different scenarios—such as planting dates, fertiliser levels, or irrigation schedules—without real-world risks.

In the coming decade, digital twins will evolve from isolated research tools into operational systems for farm management and national policy planning. For instance, governments could use regional digital twins to forecast food supply and manage climate risk at scale. As computational costs decline, these models will become increasingly accessible to cooperatives and agribusiness clusters, enhancing strategic decision-making and resource efficiency across the agricultural sector.

3. Integration of AI with Genomics and Biotechnology

The intersection of AI with genomic data and biotechnology marks another transformative pathway. Machine-learning algorithms already analyse vast genomic datasets to predict optimal gene combinations for drought tolerance, pest resistance, and nutrient efficiency (Voss-Fels, Stahl, & Hickey, 2019). In the near future, this synergy will enable precision breeding at unprecedented speed and accuracy.

AI will also play a vital role in microbiome engineering and gene-editing validation, allowing scientists to design crop varieties suited to local environmental conditions and consumer preferences. These developments will help close yield gaps between developed and developing nations while advancing global food security. However, the integration of AI and biotechnology also raises ethical concerns regarding genetic data ownership, requiring transparent governance and international regulatory alignment.

4. Growth of AI-Enabled Sustainable Food Systems

The future of AI in agriculture will be measured not only by yield but by its contribution to sustainability and circular food systems. AI is increasingly used to track carbon emissions, optimise resource cycles, and verify sustainability claims throughout supply chains (Kamilaris, Fonts, & Prenafeta-Boldó, 2019). This trend will strengthen consumer trust and allow farmers to monetise sustainability through carbon credits or green-labelling initiatives.

In parallel, AI-powered platforms will facilitate closed-loop systems—where waste from one production stage becomes input for another. Predictive models could, for example, use waste data to improve composting or renewable-energy generation on farms. These innovations align with the principles of climate-smart agriculture and contribute to SDGs 12 (Responsible Consumption and Production) and 13 (Climate Action).

5. Policy, Ethics, and Human–AI Collaboration

The trajectory of AI in agriculture depends as much on ethical frameworks as on technical advancement. The future will require strong data governance and regulatory policies to ensure fairness, transparency, and accountability in AI deployment (Wiseman, Sanderson, Zhang, & Jakku, 2019). Governments must define ownership rights over farm data, establish standards for algorithmic fairness, and create mechanisms for farmer participation in decision-making.

Equally important is the emergence of human–AI collaboration, where farmers and AI systems operate as co-decision makers rather than competitors. As AI systems become more autonomous, preserving human oversight will ensure contextual judgment and prevent overreliance on algorithms. Future extension services will therefore evolve into AI-facilitated knowledge networks, blending local wisdom with data-driven insights to achieve balanced innovation.

6. Inclusive Innovation and South–South Collaboration

The next phase of agricultural digitalisation will depend on global collaboration, particularly South–South partnerships among developing countries. Shared experiences and open innovation models can accelerate the adaptation of affordable AI tools tailored to local needs. Regional research hubs and cross-border data-sharing initiatives, supported by FAO and African Union frameworks, could foster the co-creation of locally relevant AI solutions.

Inclusive innovation ensures that smallholder farmers, women, and youth are not passive recipients of technology but active participants in co-design and governance. Building inclusive ecosystems will not only democratise AI adoption but also enhance cultural legitimacy and long-term sustainability.

7. Outlook: From Smart Farms to Intelligent Food Systems

In the long term, AI will evolve beyond the farm gate into a fully intelligent food system, where production, processing, logistics, and consumption are interconnected through continuous data flows. Predictive algorithms will manage global supply chains, anticipate consumer demand, and align agricultural output with nutritional goals. By linking climate data, market trends, and genetic information, AI will underpin a holistic framework for adaptive, resilient, and equitable food systems.

However, this vision will only materialise through sustained investment, collaborative policy frameworks, and ethical governance. The ultimate challenge is ensuring that AI's evolution serves humanity, not merely as an engine of efficiency but as an instrument of shared prosperity and ecological balance.

The concluding section summarises these insights, reiterating AI’s transformative potential and outlining the collaborative pathways required to ensure that innovation equitably benefits all farmers and strengthens global food security.

IX. Conclusion

This paper provides a comprehensive synthesis of how Artificial Intelligence (AI) is transforming global agriculture through enhanced productivity, sustainability, and resilience, particularly among smallholder farmers. The review reveals that AI technologies are no longer peripheral innovations but essential drivers of a new data-driven agricultural paradigm that addresses the intertwined challenges of food insecurity, resource scarcity, and climate change. By consolidating findings from 69 peer-reviewed studies and institutional reports, the paper establishes a holistic framework that links AI applications to measurable outcomes in productivity, sustainability, and socio-economic empowerment.

1. Summary of Key Findings

The analysis demonstrates that precision farming and predictive analytics have produced the most robust and replicable impacts to date. These technologies leverage sensors, IoT devices, and machine-learning models to optimise water, fertiliser, and pesticide use, achieving up to 30% yield gains and significant cost reductions (Basso & Antle, 2020; Zhang et al., 2002; van Klompenburg et al., 2020). Emerging applications in AI-driven robotics and crop breeding further accelerate efficiency and genetic resilience but remain capital-intensive, limiting access for smallholder farmers (Fountas et al., 2020; Voss-Fels et al., 2019). New frontiers such as soil microbiome analytics, blockchain-based traceability, edge computing, and digital twins promise to deepen sustainability outcomes by improving soil health, transparency, and decision autonomy (Jansson & Hofmockel, 2020; Kamilaris et al., 2019; Verdouw et al., 2021). Together, these technologies outline a continuum of AI maturity, from currently deployable tools to experimental systems poised to redefine agricultural intelligence.

2. Unique Contribution to Knowledge

Unlike prior reviews that focus narrowly on technological efficiency, this paper advances the literature by integrating technical, socio-economic, and policy dimensions of AI adoption. It introduces a systems-based perspective, illustrating how AI not only enhances farm-level productivity but also strengthens rural livelihoods, gender inclusion, and climate resilience. The comparative matrix and thematic synthesis bridge fragmented evidence across disciplines, enabling a clearer understanding of the pathways through which AI contributes to Sustainable Development Goals (SDGs 2, 8, and 13). This interdisciplinary integration represents the paper’s distinctive scholarly contribution—positioning AI not merely as a set of tools, but as a transformative ecosystem capable of restructuring the relationships between technology, farmers, and food systems.

3. Research and Policy Implications

To realise AI’s inclusive potential, the study recommends:

i. Investment in rural digital infrastructure (broadband, IoT, data centres) to enable equitable access.
ii. Development of low-cost, locally adaptable AI tools for smallholder use, supported by public–private partnerships.
iii. Strengthened data-governance frameworks ensuring farmer ownership, privacy, and fair value sharing (Wiseman et al., 2019).
iv. Capacity-building programs for digital literacy and AI maintenance to ensure sustainable adoption.
v. Cross-regional research collaborations to quantify environmental and economic outcomes under diverse agroecological conditions.

4. Call for Collaborative Action

Achieving global food security in the face of climate change demands coordinated engagement among governments, technology developers, financial institutions, and farmer cooperatives. AI’s potential will remain under-realised without inclusive strategies that link innovation with access, and efficiency with equity. By articulating the interconnections between AI technologies, smallholder empowerment, and policy frameworks, this paper provides a foundational reference for researchers and policymakers striving to bridge the digital divide in agriculture.

In sum, the study contributes to knowledge by reframing AI in agriculture as a multidimensional catalyst—one that unites innovation, sustainability, and social inclusion. When supported by evidence-based policies and equitable digital infrastructure, AI can help secure a resilient, sustainable, and food-secure future for all.

References

[1]. Ahmad, A., Liew, A. X. W., & Venturini, F. (2024). AI can empower agriculture for global food security: Challenges and prospects in developing nations. *Artificial Intelligence*, 2024. https://doi.org/10.3389/frai.2024.1328530

[2]. Al-Adhaileh, M. H., & Aldhyani, T. H. H. (2022). Artificial intelligence framework for modelling and predicting crop yield to enhance food security in Saudi Arabia. *PeerJ Computer Science*. https://doi.org/10.7717/peerj-cs.1104

[3]. Basso, B., & Antle, J. (2020). Digital agriculture to design sustainable agricultural systems. Nature Sustainability, 3(4), 254–256. https://doi.org/10.1038/s41893-020-0510-0

[4]. Ben-Daya, M., Hassini, E., & Bahroun, Z. (2019). A novel integrated production and transportation scheduling model for perishable products with a virtual shelf life. International Journal of Production Economics, 208, 145-159. https://doi.org/10.1016/j.ijpe.2018.11.017

[5]. Chlingaryan, A., Sukkarieh, S., & Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. Computers and Electronics in Agriculture, 151, 61-69. https://doi.org/10.1016/j.compag.2018.05.012

[6]. Clemen, T. (2023). The application of artificial intelligence models for food security: A review. *Agriculture*, 13(10), 2037. https://doi.org/10.3390/agriculture13102037

[7]. Erol, Z., Taşçı, F., & Musa, L. (2025). Utilisation of AI-reshaping the future of food safety, agriculture, and food security—a critical review. *Reviews in Food Science*. https://doi.org/10.1080/10408398.2024.2430749

[8]. FAO. (2017). *The future of food and agriculture – Trends and challenges*. Food and Agriculture Organisation of the United Nations. http://www.fao.org/3/a-i6583e.pdf

[9]. Farnworth, C. R., Baudron, F., Andersson, J. A., Misiko, M., Badstue, L., & Stirling, C. M. (2020). Gender and agricultural innovation in Oromia region, Ethiopia: From innovator to tempered radical. Gender, Technology and Development, 24(2), 171-193. https://doi.org/10.1080/09718524.2020.1757514

[10]. Fountas, S., Mylonas, N., Malounas, I., Rodias, E., Hellmann Santos, C., & Pekkeriet, E. (2020). Agricultural robotics for field operations. Sensors, 20(9), 2672. https://doi.org/10.3390/s20092672

[11]. Ikram, A., Arshad, M. T., & Rasheed, A. (2024). Applications of artificial intelligence (AI) in managing food quality and ensuring global food security. *Journal of Food*, 2024. https://doi.org/10.1080/19476337.2024.2393287

[12]. Jansson, J. K., & Hofmockel, K. S. (2020). Soil microbiomes and climate change. Nature Reviews Microbiology, 18(1), 35–46. https://doi.org/10.1038/s41579-019-0265-7

[13]. Jegede, A., Dada, E. G., & Alaba, F. A. (2024). Artificial intelligence of things (AIoT) solutions for sustainable agriculture and food security. *Artificial Intelligence of Things for Sustainable Development*. Retrieved from https://www.researchgate.net/profile/Abayomi-Jegede/publication/379757983_Artificial_Intelligence_of_Things_AIoT_Solutions_for_Sustainable_Agriculture_and_Food_Security/links/6618e42f66ba7e2359befa01/Artificial-Intelligence-of-Things-AIoT-Solutions-for-Sustainable-Agriculture-and-Food-Security.pdf

[14]. Kamilaris, A., Fonts, A., & Prenafeta-Boldó, F. X. (2019). The rise of blockchain technology in agriculture and food supply chains. Trends in Food Science & Technology, 91, 640–652. https://doi.org/10.1016/j.tifs.2019.07.034

[15]. Li, L., Zhang, Q., & Huang, D. (2014). A review of imaging techniques for plant phenotyping. Sensors, 14(11), 20078–20111. https://doi.org/10.3390/s141120078

[16]. Lowenberg-DeBoer, J., & Erickson, B. (2019). Setting the record straight on precision agriculture adoption. Agronomy Journal, 111(4), 1552-1569. https://doi.org/10.2134/agronj2018.12.0779

[17]. Mhlanga, D., & Reddy, P. S. (2023). The role of FinTech and AI in agriculture, towards eradicating hunger and ensuring food security. *Springer*. https://doi.org/10.1007/978-3-031-37776-1_6

[18]. Mushtaq, M. A., Ahmed, H. G. M. D., & Zeng, Y. (2024). Applications of artificial intelligence in wheat breeding for sustainable food security. *Sustainability*. https://doi.org/10.3390/su16135588

[19]. Neethirajan, S. (2020). SOLARIA—SensOr-driven resiLient and adaptive monitoRIng of farm Animals. Animals, 10(9), 1611. https://doi.org/10.3390/ani10091611

[20]. Senevirathne, S. M. P., & Chamara, R. (2020). Role of artificial intelligence in achieving global food security: A promising technology for the future. *Agriculture and Food Security*. Retrieved from https://account.sljfa.sljol.info/index.php/sljo-j-sljfa/article/view/88

[21]. Shi, W., Cao, J., Zhang, Q., Li, Y., & Xu, L. (2016). Edge computing: Vision and challenges. IEEE Internet of Things Journal, 3(5), 637-646. https://doi.org/10.1109/JIOT.2016.2579198

[22]. Spanaki, K., Karafili, E., & Sivarajah, U. (2022). Artificial intelligence and food security: Swarm intelligence of AgriTech drones for smart AgriFood operations. *Planning & Control*. Retrieved from https://eprints.soton.ac.uk/442863/1/Accepted_version_PPC_Final_Swarm_intelligence.pdf

[23]. Trendov, N. M., Varas, S., & Zeng, M. (2019). Digital technologies in agriculture and rural areas: Status report. Food and Agriculture Organization of the United Nations (FAO). Rome. http://www.fao.org/3/ca4887en/ca4887en.pdf

[24]. van Klompenburg, T., Kassahun, A., & Catal, C. (2020). Crop yield prediction using machine learning: A systematic literature review. Computers and Electronics in Agriculture, 177, 105709. https://doi.org/10.1016/j.compag.2020.105709

[25]. Verdouw, C., Tekinerdogan, B., Beulens, A., & Wolfert, S. (2021). Digital twins in smart farming. Agricultural Systems, 189, 103046. https://doi.org/10.1016/j.agsy.2020.103046

[26]. Voss-Fels, K. P., Stahl, A., & Hickey, L. T. (2019). Q&A: Modern crop breeding for future food security. BMC Biology, 17(1), 18. https://doi.org/10.1186/s12915-019-0638-4

[27]. Walter, A., Finger, R., Huber, R., & Buchmann, N. (2017). Smart farming is key to developing sustainable agriculture. Proceedings of the National Academy of Sciences, 114(24), 6148-6150. https://doi.org/10.1073/pnas.1707462114

[28]. WEF. (2018). *Innovation with a Purpose: The role of technology innovation in accelerating food systems transformation*. World Economic Forum. http://www3.weforum.org/docs/WEF_Innovation_with_a_Purpose_VF-reduced.pdf

[29]. Wiseman, L., Sanderson, J., Zhang, A., & Jakku, E. (2019). Farmers and their data: An examination of farmers' reluctance to share their data through the lens of the laws of smart farming. NJAS - Wageningen Journal of Life Sciences, 90-91, 100301. https://doi.org/10.1016/j.njas.2019.04.007

[30]. World Economic Forum (WEF). (2018). Innovation with a Purpose: The role of technology innovation in accelerating food systems transformation. http://www3.weforum.org/docs/WEF_Innovation_with_a_Purpose_VF-reduced.pdf

[31]. Zhang, N., Wang, M., & Wang, N. (2002). Precision agriculture—a worldwide overview. Computers and Electronics in Agriculture, 36(2-3), 113-132. https://doi.org/10.1016/S0168-1699(02)00096-0