



A Systematic Review of Artificial Intelligence Applications Across the Agricultural Value Chain: Opportunities, Limitations and Ethical Frontiers

Abdul Hannan R. Dalal^{1*}, Mohammed Danish Kolhar², Yuvraj Lahoti^{3*}

¹ Department of Artificial Intelligence, Vishwakarma University, Pune, Maharashtra, India

² Department of Computer Engineering, Vishwakarma University, Pune, Maharashtra, India

³ Department of Commerce & Management, Vishwakarma University, Pune, Maharashtra, India

*Corresponding Author: yuvraj.lahoti@vupune.ac.in ,
dalalabdulhannan@gmail.com

Abstract.

Climate change, declining resources, population growth and increased food demand are increasingly threatening the profitability of farming and demand greater efficiency and sustainability in production systems. Artificial Intelligence, or AI, is a technology that can affect how decisions are made, how resources are managed, and how much food can be grown in agriculture. This study is a systematic review of the various applications of AI throughout the agriculture value chain, from crop production, disease and pest detection through precision agriculture, post-harvest management, supply chain optimization, sustainability and emerging generative AI applications. Citing the PRISMA 2020 model, all literature published from 2016 to 2025 were gathered from different scientific databases and filtered according to the inclusion and exclusion criteria. There were a total of 214 records identified, 80 of which were potential full-text articles, and finally 34 articles were included in the qualitative synthesis. The results reveal that using AI technologies such as machine learning, deep learning, computer vision, robotics, and systems powered by the Internet of Things (IoT) can greatly help in the prediction of yields, disease diagnosis, smart irrigation, automation, resource optimization, and food traceability. In addition, key barriers to adoption highlighted in the review are data quality challenges, lack of digital infrastructure, hefty implementation costs, scalability problem, and issues around data ownership, transparency and fairness. Additionally, the governance and ethical challenges of the responsible and proper use of AI are explored, especially within smallholder farming communities. The study concludes that AI shows great promises concerning its contribution to agricultural productivity, sustainability, and resilience, but that the long-term effects of its use rely on the proper integration of inclusive policy, the need for explanation of the systems and their use in the field, and the adoption of governance frameworks that are suitable for actual application. The results give a complete overview of the current state of the art and future research directions for improving responsible AI integration in agriculture systems.

Keywords: Artificial intelligence, precision agriculture, agricultural value chain, machine learning, ethical AI, smart farming, systematic review.

1 Introduction

Agriculture plays a key role in human food security, economic development and sustenance of commodities production in rural areas across the world. But today's farming production systems are under growing threat of climate warming, rising population, weak and dwindling resources, land degradation, and shifting consumer preferences. Increased temperatures, variable climate and decreasing water supplies, decreasing land available for crops are ongoing changes which have a negative impact on crop production and the long-term sustainability of food production systems. Meanwhile, agricultural technologies and growing methods will be needed that can boost food production without consuming as much of our limited resources in the future. These interrelated issues have led to the increased interest in new and sustainable solutions that can enhance productivity, resource utilization, and resilience in the entire agricultural chain. The use of advanced digital technologies in modern agriculture has been pointed up by the major challenges in various parts of the world as shown in figure 1.

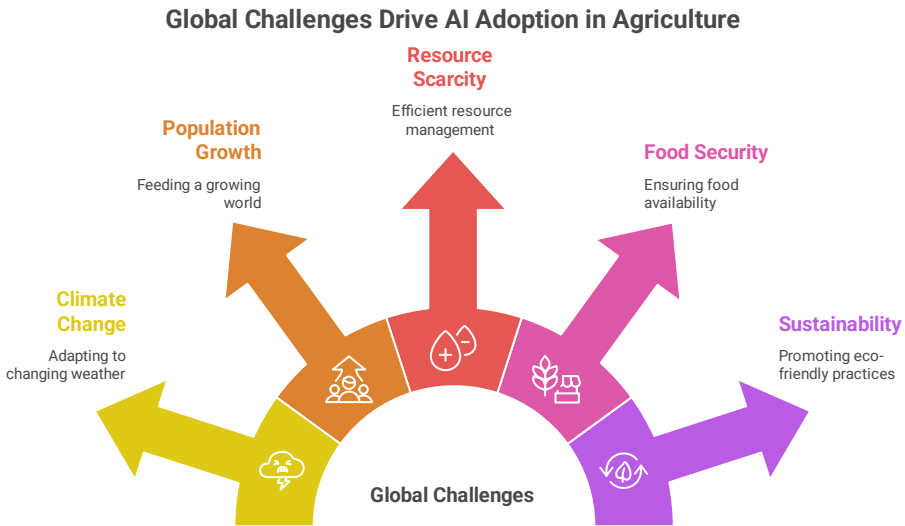


Figure 1. Global Challenges Driving AI Adoption in Agriculture

To address these challenges, AI has come up as a hopeful technology facilitator to overcome agriculture practices and to enhance decision making processes. New technologies in machine learning, deep learning, computer vision, robotics, and Internet of Things (IoT) based sensing have allowed the creation of intelligent systems to transform vast piles of agricultural data into insights that can be turned into action. These technologies can be used in various crop monitoring and yield forecasting applications, disease and pest detection, irrigation management, automated field operation and

supply chain optimization. AI can help in optimizing resource use, minimizing inefficiencies, improving productivity, and boosting the resilience of agricultural systems in response to evolving environmental and economic challenges by enabling data-driven and adaptive decision-making.

Although a lot of research has been conducted in the field of Artificial Intelligence in Agriculture, most of the studies have only considered some particular applications like crop disease detection, precision farming, smart irrigation, and/or agricultural automation. These studies will give useful information on how individual technological innovations are being used in the agriculture value chain, however there is still limited understanding of how this is being utilized throughout the value chain. Moreover, new dimensions have emerged in scope from recent developments including generative AI, sustainable agriculture, inclusion in the digital age and ethical governance, which do not get a consistent treatment across the earlier reviews. This prompts a need for more comprehensive and systemic evaluation that would span opportunities and barriers at the use of AI in agriculture.

As such, this research aims to perform a systematic review of the occurrences of different Artificial Intelligence (AI) applications presented in the agricultural value chain from 2016 to 2025. Reviewing 34 studies selected using the PRISMA framework, AI is reviewed in: crop production, disease and pest management, precision agriculture, agricultural automation, supply chain optimization, sustainability initiatives, and emerging applications of generative AI. As well as key technological developments, the re-view also critically explores adoption barriers, both infrastructural, economic and data related, as well as ethical issues. This study presents a holistic view of the state of the art, identified challenges and research opportunities for the possible future trajectory of responsible AI in agriculture.

2. Methodological Framework

2.1 Systematic Review Design

The study uses a systematic review approach to explore the use of AI throughout the agricultural value chain, focusing on the technological opportunities, constraints in implementing the technologies, and ethical issues concerning the use of AI technologies. The use of a systematic review approach was decided to provide a systematic and comprehensive evaluation of existing scholarly work, while at the same time providing transparency in study identification, selection and synthesis. This review is led by the application of AI in the different phases of agriculture such as crop production, disease detection, precision farming, post-harvest, supply chain, and governance aspects.

2.2 PRISMA Framework and Search Strategy

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework was used in the review process. As part of the review process (including identification, screening, eligibility assessment and final study inclusion), methodological transparency and consistency were achieved in accordance with this framework. This study's entire review process is depicted in Figure 2. A thorough search of literature was performed in major academic databases such as Scopus, Web of Science, Google Scholar, IEEE Xplore, SpringerLink and ScienceDirect. The search terms were chosen to reflect both the technical and the interdisciplinary studies related to agricultural AI. Common keywords were artificial intelligence in agriculture, machine learning in agriculture, precision farming, smart agriculture, deep learning for crop disease detection, agricultural value chain and ethical AI in agriculture. The search was restricted to studies published from 2016 to 2025 to ensure that the review is up-to-date with recent advancements in the field. The literature identification and screening was done following the PRISMA 2020 framework, which is illustrated below.

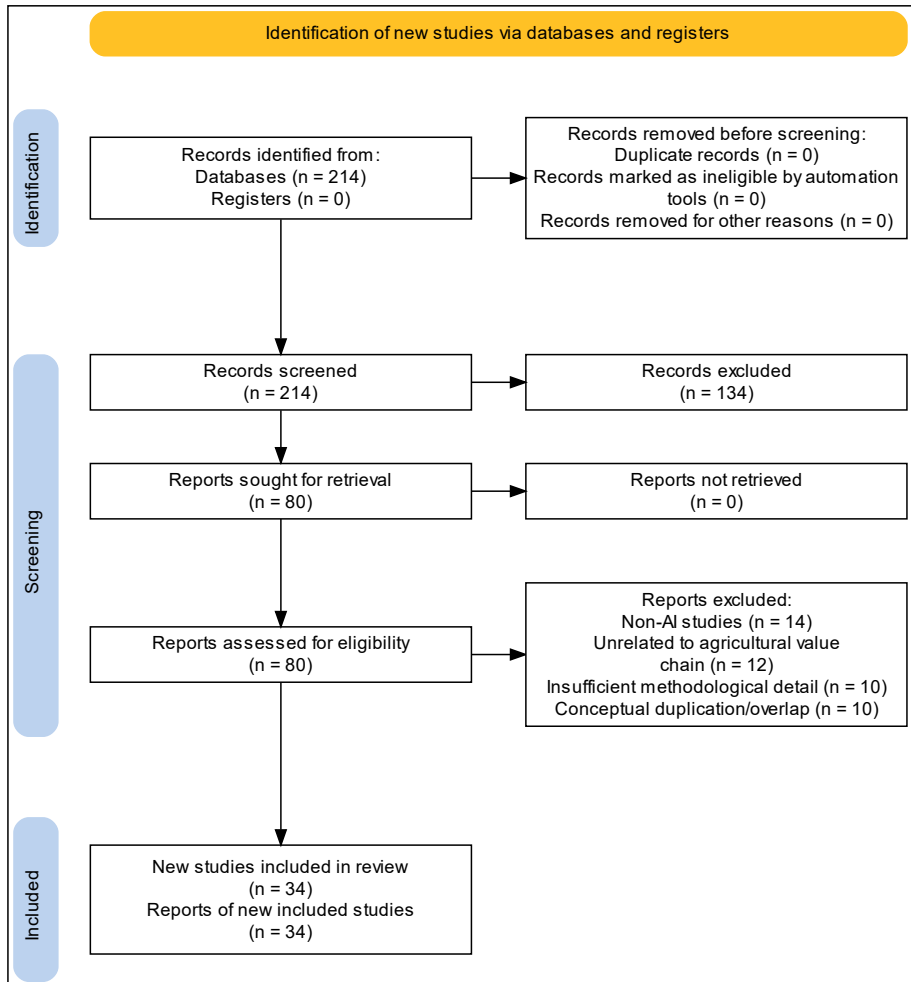


Figure 2. PRISMA Flow Diagram of the Study Selection Process

2.3 Screening Process and Study Selection Criteria

All the identified studies were subjected to a structured screening process to obtain the relevant and high-quality literature. First, based on the titles, abstracts of all the records in the boxes were preliminary screened for their relevance with regard to the aims of this review. All studies that had nothing to do with the AI app in the field of agriculture were filtered out at this stage. Full-text evaluation was done for the remaining articles after applying predefined inclusion and exclusion criteria to ensure that the articles selected were all of comparable content and methodology. The authors decided that only peer reviewed journal articles and conference papers dealing with use of artificial intelligence applications in the agricultural value chain were considered. Studies without adequate methodological information, not related directly to agriculture

activities, or without adequate AI component were not included. Database searches yielded a total of 214 records as shown in figure 2 below. After screening the titles and abstracts, 134 were excluded and 80 were further evaluated using full text screening. Following specific criteria for selection, 46 studies were excluded because they were found to be of minor relevance, methodological issues, and/or overlap with other studies chosen. As a result, 34 studies met all the selection criteria and were incorporated into the qualitative synthesis.

2.4 Thematic Coding and Analytical Classification

After final selection, the included studies were analyzed using a thematic coding approach. Each study was reviewed and categorized according to publication year, research focus, AI technique applied, agricultural stage addressed, key findings, and reported limitations. Based on this coding process, the selected literature was grouped into major thematic domains, including:

- crop production and yield prediction,
- disease and pest detection,
- precision agriculture and IoT,
- agricultural robotics and automation,
- post-harvest management,
- supply chain and traceability,
- sustainability-focused AI applications,
- ethical and governance perspectives, and
- emerging generative AI applications.

This thematic classification enabled cross-comparison of AI applications across the agricultural value chain and formed the analytical basis for the literature synthesis and discussion presented in the following sections.

3. Evolution of Artificial Intelligence in Agriculture: Research Landscape and Thematic Trends

3.1 Foundational Development of AI in Agricultural Research

There is a history of AI use in agricultural research. AI developed to become a core component in agricultural research. The application of artificial intelligence in agriculture has evolved from initial explorations and computational studies into a significant transformative technology that is now widely integrated into contemporary agricultural practices. The focus in the initial research has been, among other on the application of machine learning for prediction, classification and decision support with agricultural data of the crop, soil, weather and farm operations. As more and more data was available and computational power grew larger over time, the use of AI beyond a mere digital tool and changed to be a valuable driver of intelligent and data-informed agriculture.

The beginnings of this transition are the foundations set by early studies. Liakos et al. [1] emphasized the application of machine learning in crop monitoring, soil analysis, management of live animals, and prediction of yields. Further mining of the research literature by Kamilaris and Prenafeta-Boldú [10] revealed that deep learning was gaining recognition and momentum in applying to agricultural image analysis, remote sensing and crop analytics, while Benos et al. [8] presented the general applications of advanced machine learning methods within precision agriculture. In total, these studies underline the development of agricultural AI technology from single-location decision models to multi-levels technology-adaptable and automated systems and underscore the role of AI in shaping technology-enabled agricultural development in a sustainable and resilient way.

3.2 Expansion of AI Across Agricultural Production Systems

As the technologies of artificial intelligence progressed, they began to be used more extensively in the main production systems in agriculture. The use of predictive modelling for estimating crops has grown into a wider suite of intelligent technologies that can be used in the crop growing process, during irrigation, monitoring, harvesting and in the field to make decisions. The ability to integrate machine learning, deep learning, computer vision, sensor networks, and IoT-based systems has paved the way for this transformation, transforming agriculture into an increasingly data-driven and responsive industry. Research by Talaviya et al. [2] as well as Khanna and Kaur [9] and Babar and Akan [15] show the potential for using AI in irrigation systems to optimize water usage, for smart sensing to unlock the potential for precision farming and for connected farm monitoring systems to support informed agriculture decisions. All of these innovations demonstrate pave-the-way developments from the traditional reactive farming to the predictive and precision farming. Meanwhile, AI has become more integral to plant monitoring and agricultural robotic automation. Applying these deep learning models, early detection of plant disease diagnosis using images proved to be effective in assisting timely treatment and minimizing crop losses. Central to the value and promise of AI for disease classification, symptom identification and crop surveillance, are key contributions by Mohanty, et al [12] which demonstrated new capabilities across these domains in the context of disease recognition, Ferentinos [11] on symptom recognition, Too, et al [13] on the generalization of real-world models, Brahimi, et al [14] on agricultural emissions estimation and Majdalawieh, et al [27] on AI applied to agriculture. In addition to crop monitoring, AI has greatly speeded up the development of agricultural robots and automated systems. Bechar and Vigneault [21], Gera et al. [28] and Saiz-Rubio and Rovira-Más [31] demonstrate the integration of various arms of robotics, monitoring with unmanned aerial vehicles, development of machine vision systems, and mechanization into modern farming. All these studies suggest that AI is now an operational technology that is part of the agriculture production system.

3.3 AI Beyond Production: Supply Chains, Sustainability, and Governance

AI is not only a tool for applying technology to (agricultural) field production, but its application to agri-food systems is of growing importance as revealed by recent research. Although the initial applications of AI in agriculture were primarily related to crop monitoring and precision farming, this implementation is now gradually spreading through the post-harvest management, logistics and traceability, sustainability planning and decision making across the agricultural value chain. The applications of AI in logistics planning, market prediction, stock management, and food processing as well as distribution management are shown in studies by Ganeshkumar et al. [3], Reitano et al. [4] and Assimakopoulos et al. [5]. Both of these developments reflect a wider trend away from automation on the farm, towards value-chain intelligence – the use of AI to support the co-ordination of the many interconnected processes in the agricultural, commercial and consumer ends of the chain. Food traceability is also another emerging sector of development, where AI combined with blockchain and digital monitoring systems increasingly can enhance visibility of the supply chain, traceability, product quality assurance and consumer trust [16, 33, 17]. The literature also emphasizes the importance of AI in sustainable agriculture and the potential for long-term transformation, in addition to its impact on improving agricultural operations. The applications of AI as highlighted by Wu and Zhong [23] significantly contribute to climate resilience, sustainable use of resources, and future crop development, as well as in sustainable crop management, maximizing productivity, and minimizing environmental stress as noted by Chaudhary et al. [24] and Aijaz et al. [25]. At the same time, others, including Klerkx et al. [22], Klerkx and Rose [29] and Bronson [30] emphasize technologies' inclusive adoption, inf Farmers involvement, establishment of trust and responsible governance. The combined results of these studies indicate that the sustainability, accessibility, and the creation of a sustainable policy are crucial for the future of agricultural AI, as these elements will have to work together with technical innovations to facilitate wide-spread adoption.

3.4 Emerging Directions and Future Research Trends

New studies show that AI-driven solutions are transforming farming beyond automation into more adaptable, inclusive, and intelligent farming systems. Whereas, previous research has tended to cover within-farm productivity and operational efficiency, recent research interests have shifted to consider the role of AI in supporting sustainability, resilience planning, farmer decision making and for the longer-term agricultural transformation. It marks a wider change in how AI is understood in agriculture, beyond its role as simply a technology; as a more complex socio-technical system that is influencing the future of agri-food production. Generative Artificial Intelligence (GenAI) seems to be one of the most rapidly evolving sectors in this revolution. It offers applications across the entire agri-food value chain, particularly in the form of multilingual advisory chatbots, automated reporting, synthetic generation of agriculture data and AI-supported knowledge assistance, Krupitzer [6] emphasized. Likewise, Bhat et al. [7]

found that application of AI-powered digital platforms in planning agribusinesses, knowledge management and agribusiness forecasting was growing, indicating that generative AI could be one of the important next steps as part of agricultural innovation system. Simultaneously, AI implementation and the use of AI have been highlighted in the recent literature with an emphasis on responsible, inclusive, and human AI usage. Issues regarding who should own the data, fairness, bias in algorithms, accountability, and autonomy of farmers are increasingly central to agricultural AI research. Floridi and Cowls [18] and Jobin et al. [19] offer general frameworks of ethical foundations of trustworthy AI while Gardezi et al. [34] demonstrate specific roles of trust, explainability, and data control for farmer acceptance of AI system. However, El Bilali and Allahyari [32] do point out that digital technology should not be considered in isolation as it can further fuel inequality with its unequal access if not embraced with a spirit of inclusiveness. Going forward there are more and more ideas that refer to explainable AI, participatory technology design, open agricultural data and with a special focus on agriculture, governance models adapted to the reality of agriculture. In general, the literature indicates that the socio-technical deployment of the AI technologies for agriculture will depend on the transparency, accessibility, sustainability, and relevance of the technologies to different agriculture communities. To give a structured overview of the literature reviewed the selected studies are sorted in Table 1 into different categories based on the rest of the reviewed literature: AI-methodology, agricultural domain/crop and value chain stage, key research contributions. In this classification, we naturally separated the use of AI by system functions, from crop production and disease detection, to supply chain management, sustainability and governance of AI and emerging generative use of AI in agriculture.

Table 1. Comprehensive Literature Mapping of AI Applications Across the Agricultural Value Chain

Ref.	AI Methodology / Technology	Target Crop / Domain	Value Chain Stage	Key Contribution
[1]	Machine Learning	General Agriculture	Production	ML applications in agriculture
[2]	AI-based Optimization	Crop Production	Production	Irrigation and pesticide optimization
[3]	AI Analytics	Agricultural Value Chain	Multiple Stages	AI across agricultural value chain
[4]	AI & Predictive Analytics	Agri-Food Supply Chain	Post-Harvest & Distribution	Supply chain optimization
[5]	AI Tools & Analytics	Agricultural Systems	Multiple Stages	Status and prospects of AI tools
[6]	Generative AI	Agri-Food Systems	Advisory & Decision Support	Generative AI opportunities

Ref.	AI Methodology / Technology	Target Crop / Domain	Value Chain Stage	Key Contribution
[7]	AI-driven Strategic Systems	Agribusiness	Management & Planning	AI in agribusiness decision-making
[8]	Machine Learning	General Agriculture	Production	Comprehensive ML review
[9]	IoT + AI	Precision Agriculture	Production	Smart farming systems
[10]	Deep Learning	General Agriculture	Production	Deep learning survey
[11]	Deep Learning (CNN)	Plant Diseases	Crop Protection	Disease diagnosis models
[12]	Deep Learning (CNN)	Multiple Crops	Crop Protection	Image-based disease detection
[13]	Transfer Learning	Plant Diseases	Crop Protection	Fine-tuned disease classification
[14]	Deep Learning	Tomato	Crop Protection	Disease classification and visualization
[15]	Internet of Everything (IoE) + AI	Smart Farms	Precision Agriculture	Intelligent farm monitoring
[16]	Blockchain + AI Ecosystems	Food Industry	Traceability	Food supply chain transparency
[17]	AI-enabled Traceability Systems	Organic Food	Consumer & Distribution	Consumer trust enhancement
[18]	Ethical AI Frameworks	Society & AI Governance	Governance	Principles for responsible AI
[19]	AI Ethics Frameworks	AI Governance	Governance	Global AI ethics guidelines
[20]	Trustworthy AI	AI Systems	Governance	Ethics and reliability
[21]	Agricultural Robotics	Multiple Crops	Production & Harvesting	Farm robotics and automation
[22]	Digital Agriculture	Agriculture 4.0	Multiple Stages	Social dimensions of smart farming
[23]	AI for Sustainability	Sustainable Agriculture	Sustainability	Socio-technical roadmap
[24]	AI Models	Horticulture	Production	Sustainable horticultural systems
[25]	AI-based Agricultural Systems	Crop Production	Production	Productivity and sustainability

Ref.	AI Methodology / Technology	Target Crop / Domain	Value Chain Stage	Key Contribution
[26]	IoT + AI Smart Sensing	Agriculture	Monitoring & Production	Smart sensing technologies
[27]	Machine Learning & Deep Learning	Crop Diseases	Crop Protection	Precision disease detection
[28]	AI & Industry 4.0 Technologies	Smart Farming	Production	Agriculture 4.0 applications
[29]	Agriculture 4.0 Technologies	Food Systems	Governance & Strategy	Responsible technology adoption
[30]	Responsible Digital Agriculture	Digital Farming	Governance	Equity and innovation concerns
[31]	Agriculture 5.0	Crop Data Management	Production & Monitoring	Data-driven farming systems
[32]	ICT & Digital Technologies	Sustainable Agriculture	Sustainability	Technology for sustainability transition
[33]	Blockchain Technology	Agri-Food Systems	Traceability & Distribution	Blockchain-enabled value chains
[34]	AI Adoption & Trust Models	Farming Communities	Governance & Adoption	Building trust in AI systems

4. AI Applications Across the Agricultural Value Chain

AI technology from a farm decision-support tool has grown to fulfil a range of functions across the different parts of the agricultural value chain. Beyond the scope of crop surveillance and yield estimation, AI finds its use in both pre-production planning and post-harvest logistics, tracing and market intelligence. AI applications now span from crop monitoring and yield estimation to pre-production planning and post-production logistics, traceability, and market intelligence. The advances in machine learning, deep learning, computer vision, robotics, predictive analytics and IoT with sensing technologies have made agriculture increasingly data driven, responsive and connected. The AI technologies now affect almost every part of agricultural activities, leading to an increase in efficiency, sustainability, and decision-making within the agri-food system, as can be seen in Figure 3.

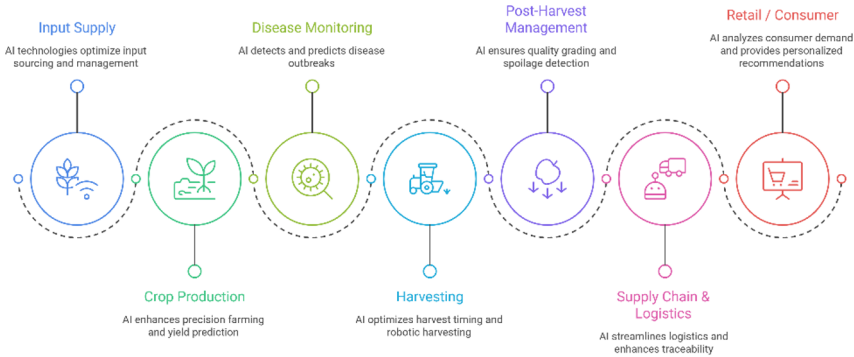


Figure 3. Agricultural Value Chain AI Framework

4.1 Crop Production and Yield Prediction

One of the areas in agriculture with the most extensive AI application research is in crop production. By leveraging historical crop data and other factors like soil properties, weather patterns, and satellite imagery, AI algorithms can analyze past production patterns and provide reliable predictions for future output, helping farmers make informed decisions about crop cultivation and yields. The machine learning algorithms like random forest, support vector machines and artificial neural network are extensively used for yield prediction and crop classification. The systems give farmers the predictive power to make optimal planting plans, predict a perfect nutrient management program, identify the perfect timing for inputs, and just more; more than what they could predict or estimate from traditional methods. AI-driven forecasting has been shown to have a significant impact on enhancing agricultural productivity and minimizing uncertainty in decision-making [1], [8], [25].

4.2 Disease and Pest Surveillance

Quick detection of plant diseases and pest infestations are critical for minimizing plant losses and productivity. This field, which has been greatly enhanced by AI's image-based diagnosis and automated field surveillance systems, is another space. Among the models, deep learning models such as convolutional neural networks (CNNs) can achieve high classification accuracy for visible symptom in leaves, stems and fruits. These systems are now being used in mobile applications, drone-based platforms for crop imaging and farm monitoring systems. AI technology aids in disease identification for quicker intervention and sported pesticide application, thus minimizing economic losses. The performance of this model in real-world conditions, however, continues to be a research challenge [11, 12, 13, 27].

4.3 Precision Agriculture and Smart Irrigation

Precision agriculture is one of the most market-ready applications of artificial intelligence in agriculture. AI-equipped sensors, remote sensing, environmental monitoring, and predictive analysis enable the management of inputs from agriculture, such as water, fertilizers and pesticides with very good accuracy. Smart irrigation solutions employ real-time soil moisture and meteorological and crop data, allowing irrigation to be automated and optimized for water use to minimize wastage by varying when and how water is applied based on the available ground state and weather conditions and crop status. Additionally, AI has the potential to provide field-level variability analysis, which will enable farmers to apply resources to only certain parts of their fields when necessary. Especially these technologies come into focus in water-scarce agricultural areas where sustainability and resource optimization are of great importance [2], [9], [15].

4.4 Robotics and Automated Harvesting

AI has also helped enhance intelligent agricultural robotics and automation systems, which help minimize reliance on labor, increase efficiency and precision in operation. From agricultural production systems, robotic harvesters, autonomous tractors, UAV (Unmanned Aerial Vehicle) based crop surveillance solutions and machine vision-based sorting systems are being investigated. The technologies can also do repetitive activities like planting to harvesting, spraying, grading, and monitoring more consistently and in a faster way. This is especially relevant in areas where there's a shortage of labor, as well as excellent operational costs. Although they have the potential to be widely deployed, high energy and upkeep costs continue to be significant challenges [21, 28, 31].

4.5 Post-Harvest Management

Post-Harvest losses remain a serious problem in agriculture and more especially in perishable food value chain. The AI use in post-harvest management is on quality assessment, sorting and grading, optimization of the storage process and prediction of spoilage. Computer vision systems are becoming widely adopted to classify produce by shape, color, ripeness and observed defects and predictive analytics are used to predict shelf life and storage conditions. The applications take the quality control, waste reduction and enhancing the market value up the agricultural value chain. AI-powered post-harvest solutions also improve efficiency in the realm of food processing and packaging operations.

4.6 Supply Chain and Food Traceability

The applications of AI are not only limited in farm production; the applications are expanding throughout the supply chain, which involves optimizing logistics, estimating prices and demand, managing inventory, and tracking products faster. Predictive models are leveraged to forecast market demands and maximize optimization of transportation planning; blockchain based AI systems enable traceability of food chains from

start to finish. They enhance transparency, food safety and accountability in the supply chain for both producers and distributors, retailers and consumers. Another field in which AI traceability solutions offer promise to boost consumers' confidence in farmer certification and organic agriculture is food of origin and flows visibility [4], [16], [17], [33].

4.7 Generative AI and Emerging Applications

Generative AI is one of the latest and fastest evolving sectors in agriculture innovation. While predictive AI systems are used for classification or forecasting, generative AI can be used to facilitate content creation, assistant functions for conversations, knowledge retrieval, and automated advice. Now some emerging applications include a multi-lingual farmer-support chatbot, generating reports with automated tools, developing synthetic datasets for agriculture, and AI-based farm decision support systems. Both these tools have potential for enhancing agricultural knowledge sharing, particularly in agricultural areas where technical advisory services are scarce. While in an early phase of deployment, GenAI is becoming an important part of future-smart components of intelligent agricultural ecosystems [6], [7]. As per literature reviewed, the AI has become an integral part of the agricultural value chain and has contributed to the overall efficiency of agricultural production as well as agri-food system management. The AI use cases are spread across the application domain and to an extent on the level of maturity of the technology, but nonetheless influence the agriculture in its various facets, allowing more precise, more automated and more adaptive systems, responding to the dynamics of the environment and the economy. As shown in Figure 3, the agricultural value chain for producing crops, monitoring diseases, post-harvest management, logistics, and consumer application, are all interconnected and impacted by artificial intelligence technologies. Table 2 analyses applications of AI across the Agricultural Value Chain

Table 2. Analysis of AI Applications Across the Agricultural Value Chain

Agri- cul- tural Stage	AI Technol- ogy Used	Major Ap- plications	Key Limita- tions	AI Value-Addition	Refer- ences
Crop Produc- tion	ML, ANN, CNN	Yield predic- tion, crop monitoring	Dataset variabil- ity and climate uncertainty	Improved produc- tivity and forecasting accuracy	[1], [8], [25]
Preci- sion Ir- rigation	IoT, Edge AI	Smart irriga- tion schedul- ing	Connectivity and infrastruc- ture dependency	Water conservation and resource effi- ciency	[2], [9], [15]
Disease Detec- tion	Deep Learn- ing, CNN	Plant disease diagnosis	Field-level gen- eralisation chal- lenges	Early disease identifi- cation and crop pro- tection	[11], [12], [13], [27]

Agri-cultural Stage	AI Technology Used	Major Applications	Key Limitations	AI Value-Addition	References
Agri-cultural Robotics	Robotics, Computer Vision	Autonomous harvesting and monitoring	High implementation cost	Reduced labour dependency and automation	[21], [28], [31]
Supply Chain Management	ML, Predictive Analytics	Demand forecasting and logistics optimisation	Integration complexity	Improved operational efficiency	[3], [4], [5]
Food Traceability	Blockchain + AI	Supply chain transparency	Interoperability and adoption barriers	Enhanced food safety and consumer trust	[16], [17], [33]
Sustainable Agriculture	Smart sensing, AI analytics	Resource optimisation and environmental monitoring	Rural infrastructure limitations	Sustainable and precision farming	[23], [24], [26]
Ethical AI Governance	Explainable AI, Governance frameworks	Transparency and accountability	Lack of standardised ethical regulations	Responsible AI deployment	[18], [19], [20], [34]
Generative AI Systems	LLMs, Generative AI	Advisory chatbots and synthetic datasets	Validation immaturity and misinformation risks	Intelligent decision support	[6], [7]

5. Opportunities of Artificial Intelligence in Agriculture

In the quickly changing field of agricultural artificial intelligence, there are many chances to boost productivity, efficiency, and sustainability across the agricultural value chain by using AI. As the world of agricultural AI continues to develop, it has the ability to bring about major improvements in these areas throughout the entire agriculture process. Besides technological developments, AI gives actual solutions to major challenges in agriculture, including uncertain climate, scarce natural resources, labor shortage, and food demand. These AI-based predictive models help in decision-making at the farm level, yield estimates, and in managing crop planning by utilizing historical data, crop performance, soil characteristics, and weather patterns. Research

has shown that they can serve to optimize agricultural production and reduce uncertainty and uncertainty costs [1] [8] [25]. Meanwhile, precision agriculture systems which are controlled by artificial intelligence improve precision in resource management; they can monitor the processes in real time and make precise suggestions for watering and all other fertilization and pesticide usage, which means a reduction in wastage and water use, particularly in agriculture in crisis situations. Meanwhile, AI can be used for precision agriculture and capture what is occurring on the field in real time; providing intelligent agronomic recommendations for ag-water use, fertilizer application, pest control and more, which ultimately saves resources and minimizes waste, especially in environmental stressed agricultural areas. In addition to production applications, AI opens new doors for agricultural efficiency and sustainability by enabling real time monitoring, automation, optimization of the agriculture value chain and other applications. Technology such as drones, computer vision and sensor-based systems can help to detect disease early and implement prompt action, which results in lowered crop losses and improved field action [11], [12], [13]. Agricultural Robotics and Autonomous systems are going to augment the efficiency of labor in various activities like planting, spraying, harvesting and sorting etc., [21] and [28]. However, in addition to the farm, AI is also being harnessed for logistics planning, market predictions, food storage and management, and even food traceability, all of which contribute to improving coordination in agri-food supply chains, food quality and consumer confidence in the agri-food supply chain [4], [16], [33]. AI can support sustainable resource utilization, make resource usage more efficient and minimize waste from sustainability perspective, allowing for climate-smart agriculture [23]-[24]-[26]. In general, the literature expounds the potential that AI can add value beyond automation and its significant ability to facilitate resilient, intelligent and sustainable agricultural systems.

6. Limitations and Structural Challenges of AI Adoption in Agriculture

While AI has tremendous potential in agriculture, a few hurdles still exist that hinder the easy and widespread use of it and its effectiveness. Data Quality issues and availability are one of the major concerns. AI models require access to extensive and representative agricultural datasets but datasets are often siloed, location-specific, and controlled. Hence models that have good performance in the experimental stage may not show as high-performance when in the real farm conditions under different climatic, geographical, operational conditions [10, 27, 1]. Another significant hurdle to the use of AI is infrastructure. A host of smart agricultural systems depend on ongoing access to the Internet, cloud computing and IoT enabled systems, and live data flow. Agricultural areas, however, that are situated in rural and remote areas are often times facing poor digital infrastructure, patchy coverage and limited access to advanced technologies. These limitations may limit the performance of precision agriculture solutions and to implement the use data-based farming practices, especially for developing economies, [9, 15, 26]. People still have to pay to use these AI technologies in a wide scale, so there are economic factors also that limit their mass use. Technology that includes sensors, drones, automated machines, monitoring platforms and AI-driven decision

support systems may be costly, but the learning curve is very steep. The cost of these may be within the budget of large commercial farms but this is not the case for the smallholder farmers, who are often financially constrained to access advanced farms technologies [21], [22] & [30]. These lead to technology disparities, and can contribute to the growing existing productivity gap between farming communities. There have also been concerns about privacy, ownership, transparency and trust with the use of the data. These modern farm-to-farm AI systems gather vast amounts of data using sensors, mobile apps, and digital platforms, but come with limitations in data control and ownership rights. Data governance frameworks and transparent algorithmic decision making are vital to prompting AI adoption by farmers but remain unclear. To achieve this, the following are essential: explainable systems as essential part of a trustworthy system, responsible data management practices and governance mechanisms that safeguard farmer interests and promote innovation [18, 19, 20, 34]. Figure 4 illustrates the barriers to AI Adoption in Agriculture.

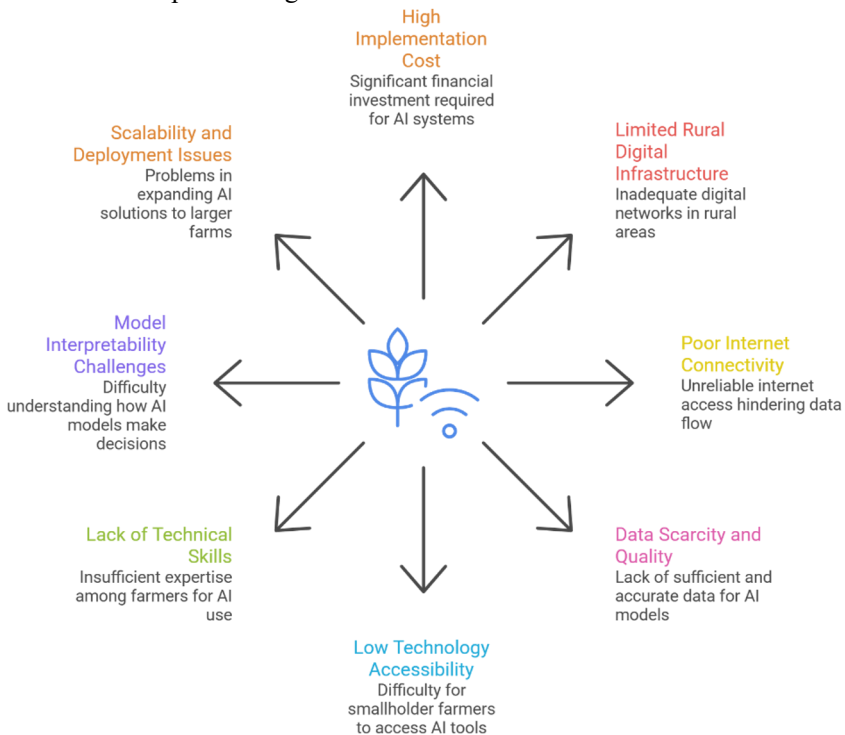


Figure 4. Barriers to AI Adoption in Agriculture

7. Ethical Frontiers and Governance Challenges of AI in Agriculture

Ethical and governance issues are different along various stages of free use of AI in the agricultural value chain. In the context of crop production or precision

agriculture, the main concerns are data ownership, data privacy and ownership of information obtained by utilizing a sensor network, drone settings, Internet of Things (IoT) and agriculture management platforms [18], [34]. Operational data is frequently produced in great quantities by farmers, but access and data-sharing are not well-defined. The other risk of algorithmic biasness and limited model generalization is evident in disease detection and in automated systems, decision-support applications, where systems based on particular datasets are used in a variety of agricultural areas in India [19, 30]. These issues are particularly relevant for smallholder farmers who might not be able to verify, challenge, or interpret AI-driven recommendations. As the use of AI in areas like supply chain analytics, traceability, and AI-driven advisory platforms grows to a more advanced stage, ethics issues intensify accordingly. Apart from maximizing transparency and the efficiency of operations, blockchain and AI may lead to questions on accountability, data governance, and also even fair access to the digital infrastructure [16], [33]. In the same way, generative AI systems can facilitate the transfer of knowledge in agriculture, but there are still unresolved issues such as the discrepancy of context, misinformation, and accuracy of the information [6, 7]. Canonicalizing the literature reviewed, a common theme across the literature is that there is not an existing agriculture specific governance framework that can address issues of 'transparency', 'explainability', 'farmer autonomy', and 'responsible data use'. Therefore, future research efforts should strive to find new regulatory standards, participatory governance structures, and explainable approaches to AI that strike a balance between technological innovation and social equity and long-term sustainability [20], [22], [29] and [32]). Technological capability alone will not be sufficient to realize long-term benefits from the use of AI in agriculture; sustainability, solid governance frameworks that promote trust, accountability and all-inclusive innovation across agricultural systems, are equally crucial.

8. Future Research Directions

The rising adoption of AI technologies in agriculture opens up pivotal opportunities for future research and development and must involve a multifaceted approach in technical, social and policy fields. Previous contributions have shown good progress for the monitoring, precision farming, disease detection and the optimization of the supply chain; future research needs to progress from innovation based on performance, and consider systems that are explainable, inclusive, scalable and able to adapt to different agricultural environments. An important research area is the design of explainable AI systems that allow farmers, agricultural advisors and policy-makers to better understand and trust the predictions that aid their decision-making, especially in regards to disease diagnosis, irrigation control, and yield predictions [18], [20]. Widely and equitably adopted affordable AI solutions that can be locally adapted, are multilingual, and are accessible by smallholder and resource-constrained farming communities are another important direction to explore [22], [30], [32]. Growing technologies like generative AI provide new opportunities in agricultural advisory services, automated reporting, knowledge dissemination and smart

decision-making processes, but need to be validated before mass deployment [6], [7]. The future might also see research on open agricultural data, collective innovation languages and interdisciplinary research by agronomists, computer scientists, policy-makers, environmental researchers and farmers [23, 26]. Meanwhile, better governance and policy processes are crucial to tackle data ownership, accountability, ethical implementation, and sustainability of agricultural AI systems [19], [29], [34]. The integration of intelligent technologies with elements of sustainability, social inclusion and farmer needs will ultimately prove to be most important for future advancement in agricultural AI in meeting the goal of conducive and responsible agricultural development, in addition to better AI algorithms.

9. Conclusion

In the era of Artificial Intelligence, agriculture technology is changing faster than ever, providing intelligent, data driven and adaptive solutions throughout the agricultural value chain. The review in this article explored the application of artificial intelligence in various areas of agricultural production and productivity, including disease identification, precision agriculture, post-harvest processes, optimization of production chains, and efforts to develop new generative AI-based systems. Results indicate technologies like machine learning, deep learning, computer vision, robotics, predictive analytics and IoT have substantially enhanced productivity, resource efficiency, decision-making and tracking throughout the operations. These advancements mirror the trend across the agricultural sector from traditional farming methods to more precise, networked and technology-based systems as better able to meet growing food production demands in the context of varying environmental conditions. Meanwhile, this review reveals that potential AI technology benefits in agriculture will rely on the ability to address significant technical, economic, infrastructural and ethical challenges. Problems of accessibility to data, data affordability, transparency, algorithms, algorithms bias, and inclusion of farmers remain to affect implementation at a large scale. In conclusion, the application of AI technologies has significant potential to transform the future of agriculture, but it is crucial to ensure their accessibility, sustainability, and social responsibility. In the future, AI may have a pivotal role to ensure resilient and sustainable agricultural systems with ongoing interdisciplinary research and innovative solutions while continuing to advocate for inclusive policies focused on AI innovation

References

1. Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, 18(8), 2674. <https://doi.org/10.3390/s18082674>
2. Talaviya, T., Shah, D., Patel, N., Yagnik, H., & Shah, M. (2020). Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artificial Intelligence in Agriculture*, 4, 58–73. <https://doi.org/10.1016/j.aiia.2020.04.002>
3. Ganeshkumar, C., Jena, S. K., Sivakumar, A., & Nambirajan, T. (2023). Artificial intelligence in agricultural value chain: Review and future directions. *Journal of Agribusiness in*

- Developing and Emerging Economies, 13(3), 379–398. <https://doi.org/10.1108/JADEE-07-2020-0140>
4. Reitano, M., Segovia, M. S., & Nayga Jr, R. M. (2025). A systematic review on the impact of Artificial Intelligence in the agri-food supply chain. *Food Policy*, 137, 102983. <https://doi.org/10.1016/j.foodpol.2025.102983>
 5. Assimakopoulos, F., Vassilakis, C., Margaris, D., Kotis, K., & Spiliotopoulos, D. (2024). Artificial intelligence tools for the agriculture value chain: Status and prospects. *Electronics*, 13(22), 4362. <https://doi.org/10.3390/electronics13224362>
 6. Krupitzer, C. (2024). Generative artificial intelligence in the agri-food value chain-overview, potential, and research challenges. *Frontiers in Food Science and Technology*, 4, 1473357. <https://doi.org/10.3389/frfst.2024.1473357>
 7. Bhat, I. A., Ansarullah, S. I., Ahmad, F., Amir, S., Sidana, S., Sinha, A., & Yazdani, G. (2025). Leveraging artificial intelligence in agribusiness: A structured review of strategic management practices and future prospects. *Discover Sustainability*, 6(1), 565. <https://doi.org/10.1007/s43621-025-01260-3>
 8. Benos, L., Tagarakis, A. C., Dolias, G., Berruto, R., Kateris, D., & Bochtis, D. (2021). Machine learning in agriculture: A comprehensive updated review. *Sensors*, 21(11), 3758. <https://doi.org/10.3390/s21113758>
 9. Khanna, A., & Kaur, S. (2019). Evolution of Internet of Things (IoT) and its significant impact in the field of Precision Agriculture. *Computers and Electronics in Agriculture*, 157, 218–231. <https://doi.org/10.1016/j.compag.2018.12.039>
 10. Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90. <https://doi.org/10.1016/j.compag.2018.02.016>
 11. Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, 145, 311–318. <https://doi.org/10.1016/j.compag.2018.01.009>
 12. Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, 7, 1419. <https://doi.org/10.3389/fpls.2016.01419>
 13. Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2019). A comparative study of fine-tuning deep learning models for plant disease identification. *Computers and Electronics in Agriculture*, 161, 272–279. <https://doi.org/10.1016/j.compag.2018.03.032>
 14. Brahimi, M., Boukhalfa, K., & Moussaoui, A. (2017). Deep learning for tomato diseases: Classification and symptoms visualization. *Applied Artificial Intelligence*, 31(4), 299–315. <https://doi.org/10.1080/08839514.2017.1315516>
 15. Babar, A. Z., & Akan, O. B. (2024). Sustainable and precision agriculture with the internet of everything (IoE). *arXiv preprint arXiv:2404.06341*. <https://doi.org/10.48550/arXiv.2404.06341>
 16. Rejeb, A., Keogh, J. G., Zailani, S., Treiblmaier, H., & Rejeb, K. (2020). Blockchain technology in the food industry: A review of potentials, challenges and future research directions. *Logistics*, 4(4), 27. <https://doi.org/10.3390/logistics4040027>
 17. Lin, X., Chang, S. C., Chou, T. H., Chen, S. C., & Ruangkanjanases, A. (2021). Consumers' intention to adopt blockchain food traceability technology towards organic food products. *International Journal of Environmental Research and Public Health*, 18(3), 912. <https://doi.org/10.3390/ijerph18030912>
 18. Floridi, L., & Cowls, J. (2022). A unified framework of five principles for AI in society. *Machine Learning and the City: Applications in Architecture and Urban Design*, 535–545. <https://doi.org/10.1002/9781119815075.ch45>

19. Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, 1(9), 389–399. <https://doi.org/10.1038/s42256-019-0088-2>
20. Ryan, M. (2020). In AI we trust: Ethics, artificial intelligence, and reliability. *Science and Engineering Ethics*, 26(5), 2749–2767. <https://doi.org/10.1007/s11948-020-00228-y>
21. Bechar, A., & Vigneault, C. (2016). Agricultural robots for field operations: Concepts and components. *Biosystems Engineering*, 149, 94–111. <https://doi.org/10.1016/j.biosystem-seng.2016.06.014>
22. Klerkx, L., Jakku, E., & Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. *NJAS: Wageningen Journal of Life Sciences*, 90(1), 1–16. <https://doi.org/10.1016/j.njas.2019.100315>
23. Wu, P., & Zhong, Y. (2025). Artificial intelligence in sustainable agriculture: Towards a socio-technical roadmap. *Smart Agricultural Technology*, 101578. <https://doi.org/10.1016/j.atech.2025.101578>
24. Chaudhary, V., Kumar, M., Chaudhary, V., Kumar, R., & Chauhan, C. (2025). Artificial intelligence in sustainable horticultural production: A systematic review. *Discover Plants*, 2(1), 372. <https://doi.org/10.1007/s44372-025-00455-2>
25. Aijaz, N., Lan, H., Raza, T., Yaqub, M., Iqbal, R., & Pathan, M. S. (2025). Artificial intelligence in agriculture: Advancing crop productivity and sustainability. *Journal of Agriculture and Food Research*, 20, 101762. <https://doi.org/10.1016/j.jafr.2025.101762>
26. Miller, T., Mikiciuk, G., Durlik, I., Mikiciuk, M., Łobodzińska, A., & Śnieg, M. (2025). The IoT and AI in agriculture: The time is now-A systematic review of smart sensing technologies. *Sensors*, 25(12), 3583. <https://doi.org/10.3390/s25123583>
27. Majdalawieh, M., Martins, C., Radi, M., Alaraj, M., & Khan, S. (2025). Precision agriculture in the age of AI: A systematic review of machine learning methods for crop disease detection. *Smart Agricultural Technology*, 101491. <https://doi.org/10.1016/j.atech.2025.101491>
28. Gera, U. K., Siddarth, D., & Singh, P. (2022). Smart farming: Industry 4.0 in agriculture using artificial intelligence. In *Artificial Intelligence for Societal Development and Global Well-Being* (pp. 211–221). IGI Global Scientific Publishing. <https://doi.org/10.4018/978-1-6684-2443-8.ch013>
29. Klerkx, L., & Rose, D. (2020). Dealing with the game-changing technologies of Agriculture 4.0: How do we manage diversity and responsibility in food system transition pathways? *Global Food Security*, 24, 100347. <https://doi.org/10.1016/j.gfs.2019.100347>
30. Bronson, K. (2019). Looking through a responsible innovation lens at uneven engagements with digital farming. *NJAS-Wageningen Journal of Life Sciences*, 90, 100294. <https://doi.org/10.1016/j.njas.2019.03.001>

31. Saiz-Rubio, V., & Rovira-Más, F. (2020). From smart farming towards agriculture 5.0: A review on crop data management. *Agronomy*, 10(2), 207. <https://doi.org/10.3390/agronomy10020207>
32. El Bilali, H., & Allahyari, M. S. (2018). Transition towards sustainability in agriculture and food systems: Role of information and communication technologies. *Information Processing in Agriculture*, 5(4), 456–464. <https://doi.org/10.1016/j.inpa.2018.06.006>
33. Zhao, G., Liu, S., Lopez, C., Lu, H., Elgueta, S., Chen, H., & Boshkoska, B. M. (2019). Blockchain technology in agri-food value chain management: A synthesis of applications, challenges and future research directions. *Computers in Industry*, 109, 83–99. <https://doi.org/10.1016/j.compind.2019.04.002>
34. Gardezi, M., Joshi, B., Rizzo, D. M., Ryan, M., Prutzer, E., Brugler, S., & Dadkhah, A. (2024). Artificial intelligence in farming: Challenges and opportunities for building trust. *Agronomy Journal*, 116(3), 1217–1228. <https://doi.org/10.1002/agj2.21353>

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

