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Recent Trends in Artificial Intelligence and IoT in the Agro-Food Industry: Smarter Farming to Safer Plates

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Highlights

- Explores how AI and IoT are transforming the agri-food sector, from farm operations to food processing and supply chain management.
- Real-world applications such as smart irrigation, disease detection, automated sorting, and predictive logistics.
- Showcases leading agri-tech start-ups and global initiatives advancing digital agriculture.
- Addresses challenges related to data privacy, infrastructure, cost, and ethical use of AI in decision-making.
- Envisions a future where AI-enabled systems support climate-resilient, transparent, and sustainable food production.

Abstract

The agri-food sector is undergoing a profound transformation, driven by the integration of Artificial Intelligence (AI) and the Internet of Things (IoT). These technologies are reshaping how food is grown, processed, distributed, and consumed bringing smarter, more sustainable, and data-driven solutions to some of agriculture's biggest challenges. From precision farming and automated food processing to smart logistics and transparent supply chains, AI and IoT are improving productivity, reducing waste, and enabling more climate-resilient practices. This review explores how these technologies are being applied across the agricultural value chain, highlights innovative start-ups and global initiatives leading the charge, and reflects on the challenges and ethical considerations that must be addressed for widespread adoption. By combining technical advancements with farmer-friendly approaches, AI and IoT hold the potential to build a more secure, efficient, and inclusive food system for the future.

Keywords - Artificial Intelligence (AI), Internet of Things (IoT), Smart Farming, Food Safety, Sustainable Agriculture

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1. Introduction

The agro-food industry responsible for producing, processing, and distributing the food we eat every day is undergoing a massive transformation. This transformation is driven by digital technologies, particularly Artificial Intelligence (AI) and the Internet of Things (IoT) (Dakhia, Russo, and Merenda, 2025). With growing global demand for food, increasing climate variability, labor shortages, and the need for sustainable farming practices, the agriculture and food sectors are looking toward smart and efficient solutions. That's where digital tools like AI and IoT come into play (Wijerathna-Yapa and Pathirana, 2022). Digital transformation in agriculture and food processing isn't just a trend it's becoming a necessity. Traditional farming methods often depend heavily on manual labor, intuition, and experience. While these methods have worked for centuries, they struggle to meet the current demands of a growing global population, stricter food safety regulations, and unpredictable climate patterns (Wang et al., 2025). Digital technologies offer a powerful solution by enabling precision, prediction, and real-time decision-making (Mustafa, Lisa, and Ali, 2025). For example, smart sensors can monitor soil health or crop moisture levels, while AI algorithms can help predict pest outbreaks or optimize irrigation schedules (Aziz et al., 2025.). In food processing units, AI and IoT can help detect product defects, maintain food safety standards, and improve traceability from farm to fork (Aghababaei et al., 2025). These digital tools help farmers and food businesses produce more with less water, less fertilizer, less waste, and less environmental impact (Reddy et al., 2025).
The world's population is expected to reach nearly 10 billion by 2050 (Lam, 2025). To meet this demand, global food production must increase significantly and ideally, without putting additional stress on already overburdened natural resources like water, soil, and biodiversity (Ruesink and Gronau, 2025). At the same time, the agriculture industry is grappling with challenges like climate change, labor shortages, inefficient supply chains, and post-harvest losses. Traditional farming methods, while essential, are not enough to address these complex problems alone (Thilakarathne et al., 2025). This is where digital transformation plays a crucial role. Technologies like Artificial Intelligence (AI), Internet of Things (IoT), machine learning, robotics, remote sensing, and big data analytics are being integrated into every stage of the agricultural and food value chain from planting and harvesting to processing, packaging, and distribution (Assimakopoulos et al., 2025). The goal is clear to make agriculture more productive, efficient, sustainable, and responsive to real-time changes in the environment and market (Balaska et al., 2023). While the term "digital transformation" might seem new, agriculture has always evolved with technology (Dayıoglu and Turker, 2021). The journey began with the First Agricultural Revolution, which introduced basic farming practices. Later, the Second Revolution brought mechanical tools like tractors and plows, which significantly improved productivity. The Green Revolution of the mid 20th century introduced chemical fertilizers, pesticides, and high-yield crop varieties, boosting food production globally (Bai, 2025). The latest phase the Fourth Agricultural Revolution is about data and connectivity. This era emphasizes smart systems that can sense, learn, and act with minimal human intervention (Chakravarty, 2025). From autonomous tractors guided by GPS to smart irrigation systems that adjust water flow based on soil moisture sensors, modern technology is making farming more data-driven than ever before (Singh and Sharma, 2025). Two of the most transformative technologies in today's agri-food landscape are Artificial Intelligence (AI) and the Internet of Things (IoT) (Devarajan, 2025). AI enables computers and machines to mimic human intelligence. In agriculture, AI can predict crop yields, detect plant diseases early through image analysis, optimize supply chains, and even assist in making climate-smart decisions. For example, AI-powered drones can scan vast areas of farmland, identifying pest outbreaks or nutrient deficiencies in real-time (Borah et al., 2025).

IoT, on the other hand, connects physical devices like sensors, machinery, and vehicles to the internet, allowing them to send and receive data (Das and Namasudra, 2025). In a smart farm, IoT devices can monitor temperature, humidity, soil quality, and crop health continuously. This data is then used to make informed decisions, such as when and where to irrigate or apply fertilizer. When combined, AI and IoT form a powerful ecosystem that brings intelligence and automation into farming practices. Farmers can monitor their fields from their smartphones, receive alerts when something goes wrong, and even automate routine tasks like feeding livestock or adjusting greenhouse conditions (Shahab et al., 2025).

The impact of digital technologies in agri-food is no longer theoretical. Across the world, real examples are proving their value: Precision agriculture uses satellite imagery and sensor data to apply inputs like water and fertilizer only where and when they are needed, reducing waste and increasing yields (Mansoor et al., 2025.). Smart logistics systems track food from farm to fork, improving food safety, reducing spoilage, and increasing transparency (Yin et al., 2025). Automated machinery such as robotic harvesters and autonomous tractors are solving labor shortages and improving operational efficiency (Jiang et al., 2025). Blockchain technology is being used to ensure traceability in food supply chains, giving consumers and regulators confidence in food origin and quality (Choo Yeon and Seong-Soo, 2025). These innovations are particularly important in developing countries, where smallholder farmers often lack access to traditional resources. Mobile apps, AI-powered advisory tools, and simple sensor-based irrigation systems are leveling the playing field, enabling even resource-limited farmers to benefit from digital advances. Despite the promise of digital agriculture, several hurdles remain. Many rural areas lack the internet infrastructure needed to support IoT systems. Farmers may be reluctant to adopt new technologies due to costs, lack of training, or concerns about data privacy (Gupta and Kumar Pal, 2025). Moreover, the growing reliance on technology raises ethical and social questions about data ownership, equity, and the role of automation in displacing human labor. Governments, research institutions, and private companies must work together to address these issues by providing training, subsidies, and robust data governance frameworks. Without such support, the benefits of digital agriculture risk becoming concentrated among larger agribusinesses, leaving small farmers behind.

This review aims to explore how digital technologies, particularly AI and IoT, are reshaping the agri-food sector. It focuses on recent innovations, real-world applications, benefits, and limitations. The goal is to provide a comprehensive overview of: The role of AI and IoT in precision farming, supply chain optimization, and food quality control. How these technologies contribute to sustainability, food security, and climate resilience. The barriers to adoption and strategies for promoting inclusive digital transformation. By synthesizing current research and case studies, this review serves as a guide for researchers, policymakers, agri-tech companies, and practitioners seeking to understand and navigate the digital future of agriculture.

2. Overview of AI and IoT Technologies

Artificial Intelligence (AI) is the science of making machines “smart.” It involves teaching computers to perform tasks that usually require human thinking such as recognizing patterns, learning from experience, making decisions, or understanding language (Chen et al., 2020). AI is like an umbrella under which several other related technologies fall, including Machine Learning (ML) and Deep Learning (DL). Machine Learning (ML) is a branch of AI where machines are trained to learn from data. For example, if you show a computer thousands of images of healthy and diseased crops, it can learn to recognize the difference and predict problems in future images without being explicitly programmed for every scenario (Goodfellow, Bengio, and Courville, 2016). Deep Learning (DL) goes a step further. Inspired by the structure of the human brain, it uses layered networks (called neural networks) to analyze complex data. Deep learning is what powers things like facial recognition, voice assistants, and advanced image classification making it especially useful in analyzing drone imagery or plant disease symptoms in agriculture (LeCun, Bengio, and Hinton, 2015). Together, these technologies allow computers and devices to "understand" what’s happening and make suggestions or take action—whether it's forecasting crop yields, optimizing irrigation, or sorting fruits on a conveyor belt (Kamilaris et al., 2018). The Internet of Things, or IoT, is reshaping how we think about modern farming. At its core, IoT refers to a network of physical devices things like sensors in the soil, cameras in greenhouses, weather stations on the field's edge, or even GPS-enabled tractors—that are all connected to the internet (Atzori, Iera, and Morabito, 2010). These devices constantly collect and exchange data, allowing farming systems to monitor conditions, respond automatically, or notify users when something needs attention. In simple terms, IoT gives "eyes and ears" to machines, enabling them to observe the world around them and act accordingly (Wolfert et al., 2017).

In agriculture, IoT applications include soil sensors monitoring moisture/nutrients, weather stations providing hyper-local insights, and smart collars tracking livestock health (Li, Wang, and Zhang, 2020). Even irrigation systems can be automated, activating based on actual soil needs rather than fixed schedules (Jayaraman et al., 2016). The IoT system operates via a four-layer architecture: sensing (data collection), network (transmission), processing (analysis), and application (action) layers (Gubbi et al., 2013). For instance, an alert might be sent to a farmer's phone when a cow shows signs of illness, or a drone may be activated to spray a specific crop area. The full potential of IoT is realized when combined with AI, forming AI-IoT (Artificial Intelligence of Things). This fusion enables devices to both collect and analyze data, then make decisions often in real time (Zhou et al., 2020). Take a smart greenhouse: sensors detect temperature, humidity, and light. AI compares this with optimal crop conditions and can activate cooling fans automatically if needed (Patel and Patel, 2016).

AI - IoT detects plant diseases before symptoms are visible, monitors the supply chain to reduce spoilage, and enables precise harvest predictions using real-time data and predictive modeling (Pantelopoulos and Bourbakis, 2010; Shankaran, Guntupalli, and Volmer, 2015). Livestock feeding and health monitoring are becoming automated too, improving efficiency and welfare (Aqeel-ur-Rehman et al., 2014). Efficiency is a major benefit. Decisions are fact-based: irrigation is targeted, reducing water use; harvests are timed better, minimizing losses; and inputs like fertilizers are optimized (Zhang, Wang, and Wang, 2002). Computer vision systems can detect stress, pests, or nutrient issues early, using drone/satellite imagery (Kamilaris et al., 2018). Food safety and traceability improve as well. Sensors monitor conditions through the supply chain, and blockchain can track produce from farm to market (Tian, 2017). For small farmers, mobile AI tools offer weather forecasts, market trends, and tailored crop advice even on basic smartphones (Baig et al., 2019). Affordable IoT devices are enabling digital inclusion in rural agriculture (Wolfert et al., 2017). AI-IoT systems also foster sustainability and resilience. With climate change increasing risks, real-time weather alerts, flood warnings, and long-term planning tools help farmers adapt (Gebbers and Adamchuk, 2010). The accumulating data aids not just current crops but long-term research and policy decisions (Rose et al., 2016). In essence, AI-IoT gives agriculture a new lens allowing farmers to see clearly, act precisely, and farm sustainably. It's about more than machine communication; it's about creating a responsive, intelligent food system for today's challenges and tomorrow's uncertainties.

3. Applications in Precision Agriculture

Agriculture has always evolved with time, but the changes brought about by digital technology especially artificial intelligence (AI) and the Internet of Things (IoT) are unlike anything the sector has seen before (Kamilaris et al., 2018). These technologies are giving rise to a new era of precision agriculture, which allows farmers to manage their resources and crops more effectively than ever, often in real time ((Wolfert et al., 2017). This approach is not just improving efficiency but is also reshaping the entire farming experience. Instead of relying solely on intuition or historical knowledge, farmers can now make decisions based on accurate, timely data (Zhang, Wang, and Wang, 2002).

One of the most transformative applications of precision agriculture is smart irrigation. Water management has long been a challenge in farming, particularly in regions affected by erratic rainfall or drought (Jayaraman et al., 2016). Traditional irrigation practices are often inefficient, applying the same amount of water to every part of a field regardless of varying soil moisture levels. Smart irrigation systems, however, make it possible to monitor moisture levels in the soil with the help of embedded sensors and IoT-enabled devices. These systems collect real-time data about environmental conditions and send it to cloud-based platforms or mobile apps (Gubbi et al., 2013). AI tools then analyze this data and determine exactly how much water is needed, and where. As a result, water is delivered precisely to the parts of the field that need it, reducing waste and improving crop health (Li, Wang, and Zhang, 2020). Farmers using these systems have reported not only water savings but also more consistent yields and reduced energy costs. Monitoring crops throughout their growth cycle has also been revolutionized by digital tools. In traditional farming, visual inspection has been the main method of tracking crop health, but this can be time-consuming, imprecise, and sometimes too late to catch early signs of trouble (Aqeel-ur-Rehman et al., 2014). Today, crop monitoring systems use drones, satellites, and ground sensors to capture high-resolution images and environmental data across entire farms (Kamilaris et al., 2018). AI-powered algorithms analyze this information to identify stress signals in plants such as changes in leaf color, shape, or size that might indicate a nutrient deficiency, disease, or water stress (Singh et al., 2016). These insights help farmers intervene early and more precisely, rather than applying treatments uniformly or after damage has occurred. Closely related to crop monitoring is yield prediction. With the help of machine learning models, farmers can estimate how much produce a particular field will yield even before harvest. These models consider a wide range of factors such as plant health, soil condition, weather patterns, and historical yield data (Pantazi, Moshou, and Oberti, 2016). The benefits of yield prediction go beyond farming decisions it helps in planning labor, storage, transport, and even marketing strategies. Accurate forecasts reduce uncertainty and allow farmers to make better business decisions, especially in markets where timing can significantly affect prices (Liakos et al., 2018).

Another critical challenge in agriculture is pest and disease management. Insects and plant diseases can spread rapidly and cause widespread crop damage if not identified and managed promptly. Traditionally, detecting these problems relied on visual inspections or waiting for symptoms to become visible by which time the damage was often already done. With the help of computer vision technology and AI, however, farmers can now detect pest infestations and diseases at a much earlier stage. High-resolution images captured via drones or mobile phones are scanned by AI systems trained to recognize specific patterns and irregularities in leaves and stems (Mohanty, Hughes, and Salathe, 2016). These tools can identify everything from fungal infections to insect bites within seconds, and often with a level of accuracy that rivals expert agronomists. This early detection enables farmers to apply pesticides or take other corrective measures only where necessary, reducing the use of chemicals and improving sustainability (Shankaran, Guntupalli, and Volmer, 2015). Soil health, long considered the invisible foundation of good farming, has also gained new visibility through technology. Soil properties can vary widely even within the same field, affecting how well different crops grow. By using soil sensors, satellite imaging, and laboratory analysis, farmers can now assess the health of their soil in great detail (Gebbers and Adamchuk, 2010). Data such as pH, nutrient levels, organic matter content, and compaction levels are collected and used to create digital soil maps. These maps allow farmers to tailor their soil management strategies for specific zones within a field, applying fertilizers, compost, or soil amendments only where needed. This kind of targeted input reduces costs and improves long-term soil fertility, contributing to more sustainable farming practices overall (Zhang et al., 2002). Weather, always a major variable in agriculture, is another area where AI and IoT technologies are making a big impact. While no one can control the weather, accurate forecasting can help farmers prepare for it more effectively. Advanced weather forecasting systems integrate data from local IoT-enabled weather stations, satellite data, and historical climate records to generate hyper-local, short- and long-term forecasts (Rose et al., 2016). AI-based decision support tools can then turn this information into practical recommendations: when to plant, when to irrigate, when to harvest, or when to delay pesticide application due to incoming rain. These insights are often delivered directly to farmers via smartphones or alert systems, allowing for real-time, informed decisions that can prevent losses or optimize outcomes (Baig et al., 2019). What ties all of these applications together is the concept of data-driven decision-making. Precision agriculture doesn't just rely on one technology it is the result of multiple digital tools working in harmony. Sensors collect data, AI analyzes it, and IoT systems act on it or send alerts to the farmer. The result is a farm that can, in a sense, think and respond. This marks a profound shift from reactive to proactive farming. Rather than waiting for signs of trouble, farmers can now anticipate and prevent problems before they occur (Zhou et al., 2020).

These applications are not limited to large commercial farms. With the growing availability of low-cost sensors, mobile-based AI tools, and open-source platforms, small and marginal farmers are also beginning to benefit (Wolfert et al., 2017). In many regions of the world, simple mobile apps are helping farmers detect plant diseases, monitor soil health, and get personalized weather updates in local languages (Baig et al., 2019). These innovations are narrowing the digital divide and making precision agriculture more inclusive. Table 1 summarizes the key applications of AI and IoT technologies across the agri-food value chain, highlighting the specific tools involved, their functional roles, and benefits to productivity and sustainability. The impact of precision agriculture extends beyond productivity. It also contributes to environmental sustainability by reducing resource use, limiting the over-application of chemicals, and supporting biodiversity (Gebbers and Adamchuk, 2010; Liakos et al., 2018). In a world where agriculture must meet the dual demands of feeding a growing population and protecting the planet, this kind of smart farming represents a much-needed balance. At its core, precision agriculture is not about replacing farmers with machines. It's about equipping farmers with better tools to make their work easier, more efficient, and more resilient in the face of climate and market uncertainties (Rose et al., 2016). With these technologies, the age-old art of farming is being transformed into a data-informed science one that honors tradition while embracing innovation. As adoption grows and infrastructure improves, these digital tools will continue to evolve, becoming more user-friendly, affordable, and scalable. The next generation of farmers may not just walk the fields they'll fly drones, check dashboards, and interact with AI assistants. But regardless of how advanced the tools become, the goal remains the same: to grow healthy food, sustainably and smartly.

4. Applications in Livestock and Aquaculture

As the global demand for animal-based food products continues to grow, the livestock and aquaculture sectors are under increasing pressure to produce more efficiently, sustainably, and ethically (FAO, 2020). Managing large numbers of animals, ensuring their health, and maximizing productivity are not easy tasks. Traditionally, these responsibilities have relied heavily on hands-on observation and experience. But now, with the rise of digital technologies, especially Artificial Intelligence (AI) and the Internet of Things (IoT), animal farming is experiencing a transformation much like crop production (Rutten et al., 2013). One of the most significant advances in this space is the use of sensors and AI for livestock health monitoring. Just as wearable devices help people track their fitness and health, similar sensor-based devices are now used in animal farming to monitor vital signs, movement, and behavior (Berckmans, 2017). These can be collars, ear tags, or implantable sensors that collect data on heart rate, temperature, feeding habits, and physical activity. This data is continuously sent to central systems or cloud platforms where AI algorithms analyze it to detect any signs of illness or abnormality (Caja et al., 2016). In traditional farming, a sick animal might go unnoticed for hours or even days . But with smart monitoring, health issues can be flagged at a very early stage sometimes even before visible symptoms appear. This early detection is crucial not only for animal welfare but also for preventing disease outbreaks, reducing mortality rates, and minimizing the need for antibiotics (Bonizzi et al., 2021). Farmers receive alerts on their smartphones when a cow shows signs of distress, a pig stops eating, or a poultry group's behavior shifts. Instead of checking every animal manually, farmers can focus their attention exactly where it's needed, saving time and resources while improving outcomes. In poultry farms and dairy management, IoT systems have become essential tools for efficiency and consistency. In modern poultry operations, environmental factors such as temperature, humidity, lighting, and ventilation can be automatically adjusted based on real-time sensor data (Kumar et al., 2021). Even slight changes in these conditions can affect bird growth, egg production, or feed conversion rates. IoT-enabled systems ensure that the environment remains optimal around the clock without constant human intervention. These systems can be managed remotely, allowing farmers to make quick adjustments if weather conditions change or if equipment malfunctions. In dairy farming, milking machines are now integrated with digital tools that track not only milk yield but also its composition and quality. Sensors attached to dairy cows record how much milk each animal produces daily and whether there are changes in milk fat or protein levels, which can indicate stress, illness, or poor nutrition. This data-driven approach allows farmers to personalize care and feeding plans, improving both animal health and overall productivity (Wathes et al., 2008). In some systems, AI is also used to analyze movement and rumination patterns to detect the onset of lameness or heat cycles, helping with timely breeding and reducing calving intervals. Aquaculture, too, is reaping the benefits of digital transformation. Fish farming, which once relied almost entirely on visual assessments and guesswork, is now turning to IoT-enabled underwater sensors, cameras, and smart feeding systems (Li et al., 2019). Water quality is a critical parameter in aquaculture, and sensors can now measure factors like temperature, oxygen levels, pH, ammonia, and turbidity in real time (Martins et al., 2012). These values are continuously monitored and displayed on digital dashboards, helping farm operators make quick decisions to avoid fish stress or mortality. AI plays a key role here by identifying patterns in the data and predicting potential risks (Misimi et al., 2018). For instance, if oxygen levels begin to drop, automated systems can activate aerators to restore balance. Similarly, feeding systems can use AI to determine the optimal amount of feed based on fish appetite and growth stages, reducing overfeeding and waste while maximizing growth (Rosten et al., 2020). Some farms are even using underwater cameras combined with AI to visually monitor fish behavior, identify diseases, and estimate biomass (Tullo et al., 2019). These innovations not only improve fish welfare and farm profitability but also reduce the environmental footprint of aquaculture operations (Neethirajan, 2021).

A particularly interesting development in both livestock and aquaculture is the use of AI to understand and predict animal behavior (Miller-Cushon and DeVries, 2017). By analyzing movement patterns, feeding times, vocalizations, and even social interactions, AI can provide insights into the emotional and physical state of animals (Shi et al., 2021). For example, a subtle change in how a group of cattle moves around a pasture or how a school of fish swims near feeding stations can indicate discomfort, aggression, or disease (Dutta et al., 2022). These behavioral cues, which might be difficult for the human eye to interpret in real time, are picked up by machine learning models trained on large datasets (Benjamin and Yik, 2019). This level of insight opens up new possibilities for improving animal welfare and productivity simultaneously. Automated feeding systems, guided by AI and sensor data, are another powerful example of how precision can lead to better outcomes. Instead of following fixed feeding schedules or applying the same ration across the entire herd or tank, smart systems tailor the quantity and timing of feed based on the specific needs of each group or even each individual animal. These systems take into account past consumption patterns, growth rates, environmental conditions, and health data. As a result, animals are better nourished, feed waste is minimized, and farmers save money on input costs. Moreover, by preventing overfeeding, farms also reduce the risk of water contamination in fish tanks and methane emissions in livestock (Shi et al., 2021). What makes these technologies especially powerful is not just the automation, but the way data from different sources health sensors, environmental monitors, feeding records, and behavior analytics can be brought together into a single, integrated system. Farmers and operators are now able to manage entire herds or fish populations with dashboards that provide a clear overview of health status, productivity metrics, and early warnings. Decision-making becomes faster, more precise, and often more humane. Despite these advancements, one of the biggest challenges is ensuring that these technologies are accessible to all types of producers not just large-scale commercial farms. Fortunately, as hardware becomes more affordable and mobile connectivity improves in rural areas, more smallholder farmers and cooperative ventures are beginning to adopt digital tools tailored to their scale and context (Bekkerman et al., 2022). Simple wearables, solar-powered IoT devices, and app-based monitoring platforms are helping democratize access to smart farming practices.

In many ways, the digital transformation of livestock and aquaculture mirrors that of crop agriculture: it shifts the focus from broad assumptions to specific insights, from reactive actions to proactive management, and from resource-heavy approaches to more efficient, sustainable ones (Jouven et al., 2021). But in animal farming, this shift carries an added ethical dimension. Healthier, happier animals not only produce better results they also align with growing consumer expectations around animal welfare and transparency in food production (Klerkx et al., 2019). As AI and IoT continue to evolve, we can expect even more sophisticated tools that help farmers understand their animals on a deeper level. From real-time stress detection to personalized feeding, the future of animal farming will be increasingly driven by empathy, insight, and data. And at its core, that's what digital agriculture is all about not replacing the farmer, but giving them better tools to care, manage, and thrive.

5. Post-Harvest Management and Food Processing

While much attention is often given to farming and food production, what happens after harvest is just as important. Once crops are harvested, or animals are processed, the journey of food is far from over. From storage and transportation to sorting, grading, processing, and packaging, every step in the post-harvest chain plays a vital role in ensuring that food reaches consumers safely, efficiently, and with its quality intact. And today, this entire chain is being reshaped by the intelligent use of technologies like Artificial Intelligence (AI), the Internet of Things (IoT), and robotics (Kollia et al., 2021; Das et al., 2025). Post-harvest losses remain one of the most significant challenges in the global food system. A considerable portion of the food produced never reaches the consumer due to spoilage, contamination, poor storage, and inefficient processing systems (da Costa et al., 2023). This is not just a matter of economic loss it's a blow to food security and environmental sustainability. However, the rise of smart technologies is helping to reduce these losses and bring greater precision and transparency into the food value chain.

One of the areas where AI is making a transformative impact is in the sorting, grading, and packaging of agricultural produce. Traditionally, these tasks were performed manually, requiring trained eyes and hands to distinguish between high- and low-quality items. It was time-consuming, prone to human error, and often inconsistent. Today, smart machines equipped with cameras, sensors, and AI algorithms are capable of identifying even the slightest variations in color, shape, size, and texture. These systems can sort fruits, vegetables, grains, or meat products within seconds, ensuring consistency, speed, and accuracy that far surpass manual methods. For example, a computer vision system can instantly detect whether an apple has bruises, if a tomato is overripe, or if a piece of meat has discolouration (Azimi and Rezaei, 2024). Based on pre-set criteria, the system then directs each item to the correct category premium, second-grade, or discard. This type of automated quality assessment not only improves efficiency but also ensures that only the best quality items move forward for packaging and distribution. And when paired with AI, these systems can learn and improve over time, adjusting to changing product conditions or new quality benchmarks. Alongside sorting and grading, AI is also being used in advanced packaging lines. Smart packaging machines can dynamically adjust packaging materials and sizes based on the type and quantity of the product, reducing material waste. Moreover, AI can optimize packaging to extend shelf life adjusting the levels of oxygen, humidity, or temperature inside packages according to the specific needs of the product (Douaki et al., 2024). Maintaining food quality goes beyond visible characteristics. Ensuring that food remains safe and traceable throughout its journey from farm to fork is equally essential. That's where AI and IoT come together to support robust quality control and traceability systems (Pandita et al., 2022). Today's consumers demand not just quality but transparency wanting to know where their food comes from, how it was handled, and whether it meets safety standards.

With IoT-enabled tracking and data collection systems, it is now possible to record every step in a product's journey right from the farm, through processing and transportation, to the retail shelf. QR codes or barcodes linked to blockchain-based systems can provide complete traceability (El-Sklar et al., 2022). Scanning these codes can reveal the farm location, harvest date, processing details, and even the temperature at which the product was stored. This level of traceability builds trust, helps brands ensure compliance with safety standards, and enables quick action if there is any issue or recall. AI also contributes to food safety by analyzing data from multiple sources storage units, transport vehicles, sensors, and more to identify risks before they become problems. For instance, if the temperature in a cold storage unit rises beyond safe limits, the system can instantly send alerts and trigger actions, such as switching to backup systems or rerouting stock. In large processing facilities, AI is used to monitor contamination risks, detect foreign particles using imaging systems, and track microbial loads through data analysis dramatically improving the ability to maintain high safety standards. Storage is a particularly vulnerable point in the food chain, especially in regions with high temperatures or poor infrastructure. Perishable goods like dairy, meat, fruits, and vegetables require precise temperature and humidity control to stay fresh. This is where IoT-based cold chain monitoring comes in. Sensors embedded in cold rooms, refrigerated trucks, or containers continuously track environmental parameters. They ensure that produce is stored and transported under optimal conditions. If a problem arises say, a sudden power cut or a door left open the system can send immediate alerts via mobile apps or cloud-based dashboards, allowing for rapid response. These monitoring systems are not limited to just detecting faults. Over time, the data they collect helps build predictive models. For instance, AI can predict which storage units are more likely to malfunction based on past performance or environmental stress. This predictive maintenance approach reduces downtime and avoids spoilage, ensuring that cold chains run more smoothly and reliably. Beyond monitoring, robotics has become a major force in food processing. In modern food factories, robots are no longer confined to heavy lifting or repetitive packaging tasks. Today, they are equipped with advanced sensing and motion capabilities that allow them to handle delicate tasks with high precision. Robotic arms can now peel, slice, sort, cook, and even decorate food products with consistent quality and speed (El-Sklar et al., 2022).

What makes these robots particularly effective is their integration with AI. They can learn the ideal shape or texture of a food item, adapt to variations in raw materials, and even identify anomalies during the process (Drijver et al., 2023). In seafood processing, for instance, robots equipped with AI can identify the type of fish, determine its size, and make precise cuts to maximize yield while reducing waste. In bakeries, robotic systems can knead dough, monitor baking conditions, and adjust in real time to ensure uniform quality. These innovations are not just about improving speed or reducing costs. Robotics and AI are helping solve labor shortages, reduce injury risks in physically demanding jobs, and maintain hygiene standards especially in processing environments that require sterile conditions. As food safety regulations become more stringent and consumer expectations continue to rise, automation offers a scalable and reliable solution (da Costa et al., 2023; Das et al., 2025). Together, these technologies are creating a post-harvest and food processing environment that is more connected, responsive, and efficient. Each stage from the moment food is harvested to the point it reaches the supermarket is becoming part of a seamless digital ecosystem. Producers, processors, transporters, and retailers can collaborate more easily, share real-time data, and respond quickly to changing conditions or demands. Importantly, these tools are becoming more accessible (Bouzembrak et al., 2019). While advanced robotics and AI systems are common in large-scale operations, more affordable, modular solutions are being developed for small and medium enterprises. Portable quality sensors, mobile-based traceability tools, and cloud-based inventory platforms are allowing even smaller processors to join the digital revolution. Despite their many advantages, the adoption of AI and IoT technologies in post-harvest systems is not without challenges (Kollia et al., 2021). Table 2 outlines some of the key barriers, risks, and ethical considerations associated with these technologies, along with potential strategies to overcome them. In the bigger picture, smart post-harvest systems contribute not only to business efficiency but also to sustainability. Reducing spoilage, optimizing logistics, and cutting down on packaging waste all have positive environmental impacts. Food that stays fresh longer and moves more efficiently through the supply chain reduces greenhouse gas emissions, supports better nutrition, and improves food availability. As the global food industry continues to grow in complexity, the need for intelligent, responsive systems becomes more pressing. The fusion of AI, IoT, and robotics in post-harvest and food processing operations offers a way forward one that enhances quality, reduces waste, and builds resilience across the supply chain. In this new landscape, technology doesn't replace human expertise; it amplifies it, providing the insights and precision needed to meet the food demands of today and tomorrow.

6. Smart Supply Chain and Logistics

The journey of food from farm to fork is long and complex. Between harvesting and reaching the consumer, food passes through a series of critical steps storage, transportation, processing, packaging, distribution, and retail. Each of these stages is vulnerable to delays, mismanagement, or spoilage, especially when fresh or perishable products are involved (Zhao et al., 2016). In a traditional supply chain, many of these steps rely on manual oversight, guesswork, or outdated records, often leading to inefficiencies and significant food waste (FAO, 2011). With the emergence of smart technologies like Artificial Intelligence (AI), the Internet of Things (IoT), and blockchain, a more intelligent, responsive, and transparent food supply chain is taking shape (Trebar et al., 2018). One of the most transformative changes in recent years is the ability to track food products in real time. Using IoT-enabled sensors and GPS technology, it's now possible to monitor the exact location and condition of goods as they move through the supply chain (Verdouw et al., 2021). Whether it's a truck transporting leafy greens or a container carrying frozen seafood, sensors embedded in packaging or transport units collect data on temperature, humidity, vibration, and light exposure, transmitting this data to cloud platforms (Aung and Chang, 2014). Such visibility is crucial for ensuring food safety and quality. For instance, if a refrigerated container's temperature rises unexpectedly, alerts can be sent to enable corrective action before spoilage occurs (Kamilaris et al., 2018). Real-time monitoring not only helps prevent damage but also builds trust across the supply chain, as buyers and regulators can verify safety standards have been met (Balamurugan et al., 2021).

Another layer of intelligence in the modern supply chain comes from predictive logistics and demand forecasting. Previously, distribution decisions were reactive and based on routine schedules. Today, AI can analyze historical and real-time data to forecast demand with high accuracy, considering factors like weather, seasonal trends, consumer behavior, and social media signals (Davenport and Ronanki, 2018). For instance, if a spike in strawberry demand is predicted due to an upcoming festival, supply chains can be adjusted to avoid shortages and reduce overstock. Blockchain technology further enhances transparency when integrated with AI and IoT. It creates a tamper-proof digital ledger that records every movement of a product across the supply chain (Francisco and Swanson, 2018). When paired with sensors and analytics, this enables comprehensive traceability. Scanning a QR code on a food item can reveal its full history from origin to storage and transit empowering consumers and ensuring accountability (Tian, 2016). In cases of contamination or recalls, the source can be traced instantly, helping ensure safety and reduce economic damage.

Food waste is another challenge being addressed through smart logistics. Approximately one-third of all food produced globally is wasted, largely due to inefficiencies in supply chains (FAO, 2011). With real-time tracking and predictive analytics, perishables nearing expiry can be rerouted or processed before spoilage. Smart shelves and inventory systems track expiration dates and stock levels to help retailers reduce waste (Rashid and Asif, 2020). AI systems can suggest rerouting surplus to nearby markets or food banks, supporting sustainability efforts. In a world facing increasing disruptions from climate change to pandemics resilient supply chains are essential. AI-powered systems can respond to blocked routes or supplier failures by offering real-time alternatives, maintaining continuity and reducing delays (Kamble et al., 2020). Shared data platforms allow stakeholders to collaborate better, enabling synchronization across the chain rather than working in silos (Trebar et al., 2018). Despite the benefits, challenges remain. Infrastructure gaps, high costs, data standardization, and low digital literacy can hinder technology adoption, especially in developing regions. But with proper investment, training, and policy support, these obstacles can be overcome (Kamilaris et al., 2018). Smart logistics are already being adopted globally, from small farmers using mobile apps to global chains implementing AI-powered inventory management (Verdouw et al., 2021). Ultimately, modern technologies enable food systems that are efficient, transparent, and sustainable. This is not just a technological shift, but a moral imperative to reduce waste, ensure food safety, and support ethical practices (Tian, 2016).

7. AI and IoT in Food Safety and Quality Assurance

Food safety is not just a regulatory requirement it is a shared responsibility and a critical trust factor between producers and consumers. In an age of global food supply chains, ensuring that food is not only fresh and nutritious but also free from contamination has become more complex than ever (WHO, 2022). Traditionally, food safety relied heavily on manual checks, laboratory testing, and paperwork-based traceability systems. While effective, these methods often fall short in managing large-scale operations and maintaining transparency (Martindale, 2017). Digital technologies especially Artificial Intelligence (AI) and the Internet of Things (IoT) are now transforming food safety and quality assurance (McFarlane and Sheffi, 2021). AI-based systems can detect food contamination by analyzing massive datasets that include information on foodborne illnesses, environmental conditions, and chemical exposure (Manning and Soon, 2019). Contaminants like *E. coli*, *Listeria*, and pesticide residues may emerge at various stages of the supply chain. AI models trained with machine learning can analyze patterns in sensor data and image recognition to detect such anomalies before they become a health hazard (Jagtap et al., 2022). For instance, hyperspectral imaging combined with AI can detect discoloration or surface abnormalities in produce, and flag batches for inspection (Lu and Peng, 2019). Similarly, cold chain violations in poultry transport can be identified in real-time using IoT sensors, allowing corrective actions before reaching consumers (Wang et al., 2021).

In food processing facilities, IoT-enabled smart sensors are used to monitor critical parameters such as temperature, moisture, pH, and microbial load. These sensors support real-time adjustments and help prevent safety breaches (Jayashree et al., 2021). For example, in dairy operations, sensors continuously track pasteurization conditions and automatically shut down systems if thresholds are breached, preventing unsafe products from moving forward in the line (Sharma et al., 2020). AI also enhances automated visual inspections using computer vision systems. Unlike manual inspection, which is affected by fatigue or subjectivity, AI-powered cameras can scan items like fruits, meats, and packaged foods for defects with higher speed and consistency (O'Sullivan et al., 2020). For example, in meat processing, AI systems can classify freshness and marbling quality using spectral analysis, improving both safety and consumer satisfaction. Food safety frameworks such as Hazard Analysis and Critical Control Points (HACCP) are now supported by digital tools. IoT-integrated HACCP systems automatically log data from critical control points, ensure compliance, and generate real-time alerts and audit trails (McEntire and Bhatt, 2020). This automation strengthens accountability and simplifies inspections. Blockchain technology adds further transparency. Every production event from farming and processing to packaging and distribution can be recorded securely on a blockchain ledger. In case of a recall or foodborne outbreak, the affected batch can be traced instantly (Kamath, 2018). Consumers too are empowered with access to traceability through QR codes on food packaging, promoting informed, ethical consumption (Galvez et al., 2018).

One of the most transformative aspects of AI and IoT is their capacity for continuous learning and process optimization. Over time, systems can identify contamination trends, optimize cleaning protocols, and adapt workflows based on seasonal or location-based risk patterns (Dani and Jabbour, 2019). These innovations are becoming more accessible even to small and medium enterprises due to falling costs and modular technology (Karwasra et al., 2023). Despite initial barriers such as high setup costs, data standardization, and cyber-risk the integration of AI, IoT, and blockchain in food safety is creating smarter, more transparent, and resilient food systems. In the future, food safety will be governed not just by periodic inspections but by continuous, intelligent surveillance powered by both human expertise and machine precision.

8. Start-ups and Global Initiatives

The transformation of agriculture and the food industry through digital technologies is not being driven solely by large corporations. In fact, some of the most impactful innovations are emerging from start-ups, research institutions, governments, and public-private collaborations (Anand and Dagar, 2022). Across the world, a new wave of agri-entrepreneurs and engineers is leveraging Artificial Intelligence (AI), the Internet of Things (IoT), drones, and data analytics to address long-standing issues in agriculture such as low productivity, fragmented supply chains, environmental degradation, and food insecurity (FAO, 2020; Klerkx et al., 2019). Start-ups, being nimble and less constrained by legacy systems, are ideally placed to experiment with emerging technologies and build innovative models. In India, platforms like Fasal, DeHaat, and CropIn are enabling precision farming for smallholders through mobile-based solutions that incorporate weather data, satellite imaging, and ground sensors (Anand and Dagar, 2022). These services offer localized crop advisories—often in regional languages—using natural language processing, making them highly accessible even in remote rural areas (Uddin et al., 2024). In the dairy sector, companies like Stellapps and MoooFarm are using wearable sensors, mobile apps, and cloud computing to digitize milk collection, monitor cattle health, and optimize cold-chain logistics (Sharma et al., 2021). Such innovations reduce waste, improve traceability, and boost farmer incomes. Outside India, start-ups like CropX and Taranis in Israel are using drone-based imaging and AI to predict pest infestations and soil nutrient levels, allowing farmers to make informed decisions before problems become visible (Kamath, 2018). In Africa, mobile platforms such as iCow and Hello Tractor have bridged gaps in extension services and farm mechanization, democratizing access to essential farm tools and veterinary care (FAO, 2020).

In Europe and North America, firms like Trace Genomics, Aerobotics, and Agremo are deploying drone technology, remote sensing, and genomic testing to provide hyper-personalized crop health insights and yield forecasting, which help reduce resource waste and improve sustainability (Verma and Tripathi, 2022). The agri-tech revolution is not only being driven by entrepreneurs. Government programs and international development agencies are playing a critical role in creating innovation-friendly ecosystems. In India, initiatives like the AgriTech Infrastructure Fund and the Digital Agriculture Mission have provided support in the form of grants, incubation, and digital infrastructure (Mehra and Sharma, 2022). Globally, the FAO, World Bank, and UNDP have initiated multi-stakeholder pilot projects in Southeast Asia, Africa, and Latin America, focusing on digital literacy, smart farming, and institutional capacity-building (FAO, 2020). One standout public-private collaboration is the Andhra Pradesh Precision Agriculture Project, supported by the World Economic Forum, where AI-enabled tools helped farmers make data-driven irrigation and crop decisions, leading to improved water use efficiency and yields (Kamath, 2018). In the Netherlands, the

Farm of the Future initiative brings together universities, policymakers, and agri-tech companies to test cutting-edge tools such as greenhouse IoT systems, autonomous tractors, and blockchain traceability solutions in real-time field settings (Klerkx et al., 2019). In Rwanda, the government's partnership with Zipline a drone delivery company—has created an innovative model for last-mile delivery of agricultural inputs and animal vaccines to hard-to-reach areas. These drones, guided by AI-based logistics systems, reduce transportation delays from days to minutes (Verma and Tripathi, 2022).

Academic institutions play a crucial role in this transformation. Indian Institutes of Technology (IITs), International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), and agricultural universities are partnering with start-ups to co-develop and test precision farming tools such as low-cost IoT kits and AI models for pest forecasting. In the U.S. and Europe, many university campuses host agri-tech accelerators that serve as launchpads for student-led ventures (Foley, 2019; Sharma et al., 2021). These collaborations have generated field-ready technologies. AI models developed in labs are now used by governments to monitor pest outbreaks and optimize resource deployment (Sharma et al., 2021). University start-ups have introduced IoT-enabled sensors for real-time crop monitoring on small farms, democratizing access to advanced farming methods (Anand and Dagar, 2022). What makes these innovations even more promising is their mission-driven orientation. Many agri-tech ventures aim to make agriculture more inclusive, climate-resilient, and transparent not just profitable (Babcock, 2021). By combining technology with empathy and purpose, these actors are reshaping agriculture to meet the interconnected challenges of climate change, soil depletion, and hunger. The future of agriculture will be shaped not only in fields and labs but also in drone hubs, coding studios, and data centers where collaboration, innovation, and sustainability intersect.

9. Challenges, Limitations, and Ethical Concerns

As promising as AI and IoT are for agriculture, large-scale adoption presents serious technical, economic, and ethical challenges (Zhang et al., 2022). One top concern is data privacy and security. Smart farms collect sensitive information soil quality, livestock behavior, crop yields that may be stored on corporate servers and used without the farmer's real consent (Singh and Sharma, 2025). Without clear regulations and farmer-centric data rights, such exploitation data-driven price manipulation or exclusion could erode trust and widen inequalities (Uddin et al., 2024). In many rural areas, connectivity and infrastructure remain unreliable. IoT systems demand stable internet, electricity, and maintenance luxuries in regions lacking basic network coverage, leading to high costs, delays, and technical breakdowns (Jabbari et al., 2024). Farmers often lack training or support to manage sensors or troubleshoot issues risks that can stall progress or make solutions unsustainable. Affordability is another obstacle. Even as device prices fall, smallholders struggle to afford initial investments, ongoing calibration, and maintenance. Technologies proven in pilot or commercial farms don't always scale to fragmented, resource-limited smallholdings (DeLay et al., 2022; Jabbari et al., 2024). Ethical and liability concerns add another dimension. AI tools might recommend irrigation or pesticide schedules, but when issues arise, who's accountable? The lack of algorithmic transparency so-called "black-box" systems shields designers and erodes farmer autonomy (Uddin et al., 2024). Labor displacement is a further worry. Autonomous machines may increase efficiency but could degrade rural livelihoods or cultural identity, particularly in communities where farming is a way of life (Daum, 2021).

Additionally, algorithmic bias when AI models are trained on unrepresentative data—may produce flawed recommendations for diverse farming contexts, while real-world weather, pests, and crops often defy pattern-based algorithms. Human intuition remains essential (Zhang et al., 2022). Finally, the sustainability of IoT itself must be considered. Smart farming depends on electricity, cloud servers, drones and thus carries a carbon footprint. Without renewable energy or circular hardware design, these tools might undermine sustainability goals (Daum, 2021). Overcoming these challenges means placing farmers at the center: they must be co-creators, not just users. Clear policies on data ownership and privacy are essential, alongside training programs, transparent AI, open standards, and decentralized governance. Only then can AI and IoT evolve in agriculture not as technologies imposed *on* farmers, but as tools developed with them smart, equitable, and truly fit for purpose (Li and Wang, 2023).

10. Future Perspectives

As the digital transformation of agriculture unfolds, we stand at the onset of a profound shift. AI and IoT have already elevated productivity and precision but the true potential lies ahead in their integration with complementary technologies, resulting in smarter, more resilient food systems . One promising convergence is AI + blockchain. Blockchain offers secure, tamper-resistant records, ideal for underpinning AI-generated forecasts and traceability data. Together, they ensure both the reliability of AI recommendations and verifiable provenance. Farmers could view AI-based yield forecasts and immediately verify seed origins, soil tests, and storage conditions via blockchain, enhancing trust and enabling full transparency from farm to consumer.

Drones + AI is another potent synergy. Unmanned Aerial Vehicles (UAVs) equipped with high-resolution multispectral or thermal sensors, combined with AI analytics, can autonomously identify and sometimes remediate crop issues, especially in remote or uneven terrain. As drone costs decrease and regulations ease, “smart scout” drones will play an even bigger role in early detection and action. Predictive agriculture, fueled by real-time AI models accessing weather, soil, market, and climate data, will become indispensable amid climate volatility. Farmers will anticipate not just respond to risks, enabling adaptive planning in the face of extreme events. Beyond cultivation, AI and IoT will drive circular and decentralized food systems. From vertical farms to smart logistics, these tools will reduce waste, optimize resource flows, and connect producers directly with consumers. Examples include AI-managed energy flows in urban farms and real-time freshness tracking in transport networks.

However, this future must embed equity and ethics: AI must not consolidate power in large agribusinesses. Instead, it should democratize access through affordable sensors, open-source tools, and mobile AI platforms tailored to marginalized smallholders. Education and capacity-building are equally vital. Digital literacy must be woven into agricultural training so farmers, extension workers, and students can understand, question, and design the tools they use. At a global scale, collaborative frameworks are needed. Governments, industry, academia, and civil society must co-create policies that balance innovation, regulation, and ethics. International cooperation will ensure shared standards, equitable access, and resilience to global challenges like climate change and food insecurity. Ultimately, the vision is an agriculture system that is efficient, transparent, just, and responsive to human and planetary needs. Technology is not the goal it is the means. The true test will be whether AI and IoT elevate both farm performance and human dignity.

11. Conclusion

The integration of AI and IoT into agriculture and food systems marks a turning point in how we grow, manage, and deliver food. These technologies offer more than just automation they bring intelligence, precision, and adaptability to every stage of the value chain. Whether it’s predicting weather-driven crop risks, tracking food from farm to shelf, or using sensors to detect contamination in real time, AI and IoT are helping farmers and food producers make better decisions with greater confidence. While the potential is vast, the journey is not without its hurdles. Digital divides, cost barriers, ethical concerns, and infrastructure gaps remain real challenges especially for small and marginal farmers. To fully realize the benefits of smart agriculture, it's essential to design systems that are not only innovative but also inclusive, affordable, and grounded in local realities. Collaboration across sectors industry, government, academia, and farming communities will be key to making this transformation meaningful and sustainable. The goal is not just to build smarter farms or faster supply chains. It's to create a food system that is more resilient to climate change, more respectful of natural resources, and more responsive to the needs of both producers and consumers. AI and IoT, when applied thoughtfully and ethically, can help us move toward that vision a future where food is not only abundant and safe, but also fair, traceable, and grown in harmony with nature.

Conflict of Interest

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Table 1: Applications of AI and IoT Across the Agri-Food Value Chain

Stage of Value Chain	Technology	Key Applications	Benefits	References
Crop Production	AI-based computer vision, IoT soil sensors	Precision irrigation, crop health monitoring	Increased yield, resource efficiency	(Kamilaris et al., 2018)
Post-Harvest Handling	IoT-enabled cold chain sensors, AI logistics	Smart storage, spoilage prediction	Reduced food loss, quality maintenance	(Rejeb et al., 2022)
Processing	AI for quality grading, automation with robotics	Automated sorting and food safety detection	Higher efficiency, consistent quality	(Misra et al., 2020)
Packaging	Smart packaging with embedded sensors	Real-time freshness tracking, traceability	Enhanced food safety, consumer trust	(Mahalik and Nambiar, 2010)
Distribution and Retail	AI for demand forecasting, IoT in logistics	Route optimization, dynamic pricing	Reduced emissions, better stock control	(Zhang et al., 2023)
Consumption and Feedback	Mobile apps, AI consumer analytics	Personalized nutrition, waste tracking	Healthier choices, reduced waste	(Chen et al., 2021)

Table 2: Challenges and Considerations in AI/IoT Adoption in Agri-Food Systems

Challenge	**Description**	**Impact**	**Proposed Solutions**	**Reference**
Data Fragmentation	Lack of standardized data formats across devices and regions	Limits integration and scaling	Promote interoperability standards	(Wolfert et al., 2017)
Digital Divide	Limited access to tech in rural/smallholder communities	Exacerbates inequality	Subsidized tech, local training	(Klerkx et al., 2019)
Cybersecurity and Data Privacy	Risks from connected devices and farm-level data leaks	Reduces user trust, risk of sabotage	Secure-by-design systems	(Zhang et al., 2022)
Cost and ROI Concerns	High upfront investment in IoT infrastructure	Low adoption in resource-poor settings	Demonstration pilots, public–private funding	(Liakos et al., 2018)
Ethical and Regulatory Gaps	Lack of frameworks for AI decision-making in food systems	Risk of bias, data misuse	Develop agro-ethics policies, multi-stakeholder regulation	(Floridi et al., 2018)