

Artificial intelligence (AI) in food safety and quality: New approach, advantages, and disadvantages

Risto Uzunov*, Aleksandra Angeleska

Faculty of Veterinary Medicine - Skopje, Ss. Cyril and Methodius University in Skopje (UKIM)

*Corresponding Author: Risto Uzunov, Faculty of Veterinary Medicine, Ss. Cyril and Methodius University in Skopje (UKIM), Lazar Pop Trajkov 5-7, Skopje1000, North Macedonia. Email: risteuzunov@fvm.ukim.edu.mk

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Abstract

The adoption of artificial intelligence (AI) within the framework of fourth industrial revolution (Industry 4.0) is reshaping contemporary food safety management by enabling a transition from predominantly reactive practices to proactive and predictive approaches. This study explores how AI-based technologies, including machine learning, computer vision, and Internet of Things (IoT) technologies, contribute to improved food safety control, quality monitoring, and supply chain traceability. The analysis indicates that AI-driven solutions outperform traditional manual methods by delivering faster and more accurate detection of contaminants, improved identification of foodborne pathogens, and more reliable shelf-life prediction. The integration of AI with blockchain further strengthens traceability mechanisms, allowing rapid identification and containment of contamination events. Nevertheless, several limitations remain, notably the limited interpretability of complex deep-learning models, substantial implementation costs, and persistent challenges related to data quality and standardization. In addition, ethical issues, such as data protection and potential algorithmic bias, highlight the importance of transparent governance frameworks. The findings suggest that optimal outcomes are achieved when AI systems operate within a human-in-the-loop model, supported by interdisciplinary expertise and harmonized global datasets. Collectively, these advancements indicate that AI has strong potential to enhance the resilience, efficiency, and transparency of the global food supply chain, supporting progress toward a zero-contamination objective.

Keywords: artificial intelligence; food safety; IoT; machine learning; sustainability; traceability

Introduction

Food safety constitutes a fundamental pillar of the global food industry and is a critical determinant of both manufacturer's reputation and economic performance. Even a single food safety incident can precipitate extensive product recalls, substantial financial losses, and enduring reputational damage, ultimately eroding consumer confidence (Grylls, 2024). Beyond commercial implications, food safety is essential for safeguarding public health. Current estimates indicate that foodborne illnesses are responsible for approximately 600 million cases of

illness and 420,000 deaths worldwide each year (Wang *et al.*, 2025; World Health Organization [WHO], 2015). Despite sustained global efforts to mitigate these risks, the incidence of foodborne disease continues to rise in many regions. Comprehensive analyses of food safety incidents have identified undeclared allergens as the most prevalent cause, followed by microbiological cross-contamination and failures in adherence to good manufacturing practices (Nazir *et al.*, 2023; Sari *et al.*, 2025).

Over the past four decades, food safety management systems have evolved with a primary focus on hazard

identification and the monitoring of scientifically validated control measures, most notably through the implementation of Hazard Analysis and Critical Control Points (HACCP) framework (Dlamini and Adetunji, 2023; Wang *et al.*, 2025). Although HACCP remains the global standard for preventive food safety management, a significant proportion of foodborne illness outbreaks continue to result from noncompliance with established procedures and suboptimal food safety behaviors among food handlers. Conventional monitoring approaches are frequently reactive, labor-intensive, and limited in coverage (Arslan, 2025; Sharman *et al.*, 2020). Techniques, such as manual sampling, microbial culturing, and periodic inspections, often require specialized infrastructure, are sample-destructive, and involve considerable delays (van Meer *et al.*, 2025). Moreover, reliance on human sensory evaluation for assessing food quality and freshness is inherently subjective and susceptible to judgment variability, commonly referred to as decision “noise” (Kahneman *et al.*, 2021).

The increasing globalization of food supply chains and the growing complexity of industrial food production have introduced new vulnerabilities that traditional food safety systems are ill equipped to manage. Modern supply chains frequently span multiple geographic regions and involve a wide range of stakeholders, increasing the number of potential contamination points and complicating traceability and accountability mechanisms (Ambikalekshmi *et al.*, 2025). Concurrently, global pressures, such as climate change and population growth—projected to reach 10 billion by 2050—demand a 70% increase in food production. This rising demand, combined with resource constraints and labor shortages, has intensified the need for automation and intelligent management solutions in agriculture and food processing (Tripathi *et al.*, 2019).

Within this evolving landscape, artificial intelligence (AI) has emerged as a transformative technology capable of modernizing food safety and quality management systems (Dhal and Kar, 2025; Palakurti, 2022). AI encompasses computational systems designed to replicate human cognitive processes, including learning, reasoning, and problem-solving. As a core driver of the fourth industrial revolution (Industry 4.0), AI leverages big data analytics and advanced algorithms to exceed the capabilities of traditional labor-dependent and manual approaches. These technologies facilitate a paradigm shift in food safety management, transitioning from reactive, testing-based approaches to proactive, predictive, and data-driven models (Arslan, 2025; Balta *et al.*, 2025; Ding *et al.*, 2023).

Key AI subdomains contributing to advancements in food safety include machine learning (ML) for pattern recognition and risk forecasting, deep learning (DL) for analyzing complex, high-dimensional datasets, computer vision (CV) for automated visual inspection, and natural language processing (NLP) for extracting insights from unstructured textual data, such as regulatory documents and consumer feedback (Ambikalekshmi *et al.*, 2025; Qian *et al.*, 2023). When combined with Internet of Things (IoT) sensors and blockchain technology, AI enables continuous real-time monitoring of environmental conditions and the creation of secure, immutable traceability records across the entire food supply chain. These integrated systems can detect deviations in critical control parameters, including temperature and humidity, and issue immediate alerts to prevent unsafe products from reaching consumers (Kowalski, 2025; Palakurti, 2022; Yin *et al.*, 2025).

Despite its considerable potential, the adoption of AI in the food sector presents notable challenges. Technical constraints, such as reduced algorithm performance in complex operational environments and the opaque “black box” nature of certain DL models, may impede regulatory acceptance and stakeholder confidence (Ambikalekshmi *et al.*, 2025). Ethical considerations related to data privacy, algorithmic bias, and workforce displacement resulting from automation must also be addressed carefully to ensure responsible and equitable implementation (Dhal and Kar, 2025; Wang *et al.*, 2025). Furthermore, the substantial financial investment required for AI-enabled infrastructure poses a significant barrier for small- and medium-size enterprises (SMEs), particularly in low- and middle-income countries (LMICs) (Ambikalekshmi *et al.*, 2025; Sari *et al.*, 2025).

The objective of this study is to provide a comprehensive review of current applications of AI in food safety and quality management. The article evaluates systematically the integration of AI-driven methodologies throughout the food supply chain, highlights their technical and managerial advantages over conventional systems, and critically examines the technical, ethical, and organizational barriers limiting widespread adoption. In addition, this review explores emerging trends and proposes a strategic roadmap to support stakeholders in leveraging AI technologies to develop a more resilient, transparent, and sustainable global food safety framework.

Artificial Intelligence in Food Safety and Quality

Transition to Industry 4.0, commonly referred to as the fourth industrial revolution, represents a fundamental

shift toward the digitalization and intelligent integration of production systems. Whereas earlier industrial paradigms emphasized mechanization (Industry 1.0), mass production enabled by electrification (Industry 2.0), and computer-based automation (Industry 3.0), Industry 4.0 is characterized by the convergence of cyber–physical systems within highly interconnected and adaptive production environments. This paradigm integrates AI, IoT, big data analytics, and cloud computing to enable continuous communication between machines, systems, and stakeholders, thereby facilitating autonomous and data-driven decision-making processes (Demiral *et al.*, 2025; Ding *et al.*, 2023; Ikram *et al.*, 2024; Kakani *et al.*, 2020).

Within the food sector, this transformation is often described as Food Industry 4.0 or Gastronomy 4.0 and marks a strategic departure from traditional, reactive, and labor-intensive inspection-based food safety practices toward a fully digitalized and intelligent management framework. Through the deployment of smart sensors, robotics, and digital twin technologies, Industry 4.0 systems are capable of emulating human cognitive functions and executing complex operational tasks by processing large volumes of heterogeneous data in real time (De Baerdemaeker *et al.*, 2023; Dhal and Kar, 2025; Kowalski, 2025).

In contrast to conventional food safety management systems (FSMS), which have traditionally relied on reactive controls and periodic batch testing, Industry 4.0-enabled infrastructures support proactive and predictive food safety strategies. By integrating real-time monitoring, advanced analytics, and predictive modeling across the entire food supply chain, these systems enhance early detection of risks and enable timely corrective actions. Ultimately, Industry 4.0 establishes a holistic and interconnected digital ecosystem that replaces fragmented manual safety checks with autonomous and continuous oversight. Leveraging real-time data streams and advanced analytical tools, the global food supply chain can transition from a predominantly reactive posture to a proactive and predictive operational model, thereby improving food safety assurance, traceability, and the overall operational efficiency from farm to fork.

New approaches

Integration of AI in food safety has progressed well beyond basic automation and now encompasses a diverse array of advanced methodologies that fundamentally reshape how food safety hazards are identified, assessed, and managed. These technologies enable continuous,

data-driven oversight and support the transition from reactive control measures to proactive and predictive food safety systems.

Machine learning and deep learning architectures

Machine learning has become a foundational tool for recognizing patterns within complex datasets associated with contamination, adulteration, and spoilage (Dhal and Kar, 2025). Conventional supervised learning models, including support vector machines (SVM) and random forest (RF), are widely applied to structured classification tasks, such as detecting pesticide residues or determining the geographical origin of food products, including white asparagus and Chinese liquor (Yin *et al.*, 2025; Zhang *et al.*, 2025). More sophisticated DL architectures—particularly convolutional neural networks (CNNs)—have transformed visual data analysis in food safety applications (Palakurti, 2022). CNN-based systems are now routinely used to automatically segment and identify bacterial colonies on agar plates and to detect microscopic defects on food surfaces, achieving significantly higher speed and accuracy compared to manual inspection methods (Yin *et al.*, 2025). In parallel, transformer-based models, such as BERT and RoBERTa, are increasingly employed to classify food safety risks using large-scale databases, including the European Union's (EU) Rapid Alert System for Food and Feed (RASFF). By analyzing the full contextual content of alert descriptions, these models have demonstrated classification accuracies of up to 97.9% (Sari *et al.*, 2025). These examples demonstrate the growing reliability and versatility of AI in food safety. While traditional models remain useful for structured tasks, DL and transformer architectures clearly offer superior performance for complex and high-dimensional datasets. However, it is important to note that these models still require careful validation and context-specific adaptation to ensure that predictions remain accurate and actionable across different food products and production environments.

Computer vision and non-destructive testing

Computer vision technologies provide a non-destructive alternative to conventional sampling-based quality assessment by applying image-processing techniques to data captured along production and processing lines. These systems play a critical role in automated sorting and grading operations, enabling real-time detection of external defects such as bruising, mold growth, and shape irregularities (Ambikalekshmi *et al.*, 2025; Kakani *et al.*, 2020; Yin *et al.*, 2025). When integrated with hyperspectral imaging (HSI), CV-based approaches extend their capabilities to internal quality assessment and the detection of chemical contaminants that are not

visible to the human eye (Adedeji *et al.*, 2024; Nikzadfar *et al.*, 2024). For example, AI-driven HSI systems have demonstrated high precision in identifying pesticide residues on spinach and detecting fecal contamination on leafy greens (Qian *et al.*, 2023; Yin *et al.*, 2025). These examples illustrate that combining CV with HSI allows AI systems to assess both external and internal food quality with high precision. While highly effective, these technologies require careful calibration and adaptation to different product types, processing conditions, and environmental factors. Overall, CV-based approaches represent a significant advancement toward automated, reliable, and non-destructive quality control in the food industry.

Natural language processing and sentiment analysis

Natural language processing has emerged as a powerful tool for extracting actionable insights from unstructured data sources, including regulatory documentation, scientific publications, and consumer-generated content (Ambikalekshmi *et al.*, 2025; Qian *et al.*, 2023). Regulatory authorities increasingly employ NLP techniques to monitor international news and surveillance reports for early indicators of outbreak of foodborne disease. Simultaneously, food businesses leverage sentiment analysis to evaluate consumer reviews on platforms, such as Amazon and TripAdvisor, enabling the identification of unreported illness cases or emerging quality concerns (Maharana *et al.*, 2019; van Meer *et al.*, 2025). These applications support near real-time surveillance and facilitate rapid intervention before minor issues escalate into widespread safety incidents (Balta *et al.*, 2025). These examples demonstrate the potential of NLP to transform the monitoring of food safety by enabling the rapid processing of large volumes of unstructured data. The effectiveness of these approaches relies on the quality and representativeness of the underlying datasets as well as on the continuous updating of models to reflect emerging risks. Overall, NLP-based systems provide a proactive framework for early detection and timely intervention, enhancing both regulatory oversight and industry responsiveness.

Internet-of-things and smart sensors

The convergence of AI with IoT technologies enables the development of digital twins that replicate the physical food supply chain in a virtual environment. IoT sensors embedded within transportation vehicles, storage facilities, and processing environments continuously monitor critical parameters, such as temperature, humidity, and volatile gas concentrations (e.g., ethylene and ammonia). These data streams are analyzed by AI models to predict spoilage dynamics, optimize logistics, and extend product's shelf life (Kowalski, 2025; Rashvand *et al.*, 2025; van Meer *et al.*, 2025). In addition, smart packaging

innovations now incorporate colorimetric indicators that respond to microbial metabolic activity. When scanned via smartphone applications, AI algorithms can rapidly assess product safety and freshness, providing consumers and regulators with immediate decision support (Gong *et al.*, 2023; Yin *et al.*, 2025). The integration of AI and IoT enables a shift from periodic inspections to continuous, predictive monitoring of the food supply chain. Accurate sensor calibration, robust data management, and real-time model updates are essential to maintain the reliability of predictive insights. By leveraging these technologies, supply chain operations can achieve higher product safety, extended shelf life of a product, and more effective decision-making for both producers and regulators.

Blockchain and trusted traceability

The integration of AI with blockchain technology facilitates the creation of decentralized, tamper-resistant ledgers that record every transaction across the food supply chain, from primary production to retail (Dhal and Kar, 2025; Kamath, 2018). AI-driven analytics applied to blockchain data enable the detection of anomalies—such as delayed data entries, temperature deviations, or irregular transaction patterns—that may signal food fraud, contamination, or improper handling. This approach has been successfully piloted by major retailers, including Walmart, allowing contaminated batches of leafy greens to be traced and isolated within seconds rather than days (Arslan, 2025; Balta *et al.*, 2025; Yin *et al.*, 2025). Thus, the combination of AI and blockchain enhances transparency and accountability throughout the supply chain, enabling faster response to potential safety breaches. Effective implementation relies on accurate and timely data entry as well as the integration of AI models capable of identifying meaningful patterns within large, decentralized datasets. Overall, this approach supports more resilient food safety management and strengthens trust among producers, regulators, and consumers.

Behavioral ai and food safety culture

An emerging area of innovation focuses on the application of AI to monitor and enhance human behavior, which remains a critical determinant of food safety performance. AI-enabled camera systems can assess employee compliance with hand hygiene protocols and the proper use of personal protective equipment (PPE), providing real-time feedback and corrective alerts. Additionally, emotion recognition and behavioral analytics are being explored to assess workplace stress and fatigue levels, enabling proactive managerial interventions to reduce the risk of safety lapses associated with human factors (Wang *et al.*, 2025). AI-driven behavioral monitoring enhances food safety by observing compliance with hygiene protocols, PPE usage, and

other critical practices in real time. When implemented effectively, these systems can identify potential risks before they escalate, allowing management to intervene proactively. By combining behavioral insights with automated alerts and training, AI contributes to a safer, more reliable, and continuously improving food production environment.

Collectively, these AI-driven methodologies replace episodic, manual oversight with continuous, intelligent monitoring systems. By integrating non-destructive sensing technologies, predictive analytics, and decentralized data management, the food sector is establishing a proactive infrastructure capable of mitigating hazards in real time. This comprehensive integration not only strengthens the physical integrity of the food supply chain but also addresses the human and environmental variables that underpin global food safety and quality assurance.

Advantages

The adoption of AI-driven systems in food safety and quality management offers substantial strategic and operational advantages that extend well beyond the capabilities of traditional inspection and control methods (Mavani *et al.*, 2021). By enabling continuous, data-driven decision-making, AI enhances accuracy, efficiency, sustainability, and risk prevention across the food supply chain.

Enhanced accuracy and consistency

Artificial intelligence-based systems deliver high levels of accuracy and consistency that are unaffected by human fatigue, cognitive bias, or subjective decision “noise” (van Meer *et al.*, 2025; Wang *et al.*, 2025). In particular, CV models have demonstrated defect and contaminant detection rates exceeding 95%, significantly outperforming human inspectors in high-throughput and time-constrained processing environments. This elevated level of precision enables the early identification and removal of substandard or hazardous products, thereby reducing downstream risks and recall events (Ambikalekshmi *et al.*, 2025; Palakurti, 2022; Yin *et al.*, 2025). Such findings highlight the potential of AI to standardize quality control processes and minimize variability introduced by human inspection. While these systems offer remarkable accuracy, their effectiveness relies on proper calibration, continuous validation, and adaptation to different product types and processing conditions. Overall, AI-based inspection represents a significant step toward more reliable and proactive food safety management.

Proactive and predictive risk management

One of the most transformative advantages of AI lies in its predictive capabilities. By integrating historical records with real-time environmental and operational data, AI systems can anticipate contamination events, equipment failures, or spoilage risks before they materialize (Arslan, 2025; Dhal and Kar, 2025). This foresight allows producers and regulatory authorities to implement preventive interventions—such as adjusting storage conditions, rerouting shipments, or increasing targeted inspections—thereby minimizing the likelihood of foodborne outbreaks and large-scale public health incidents (Balta *et al.*, 2025; Bronzwaer *et al.*, 2019). These capabilities illustrate how AI shifts food safety management from a reactive to a proactive paradigm. The success of predictive systems depends on the quality, representativeness, and timely updating of underlying datasets as well as the integration of accurate environmental and operational monitoring. By enabling anticipatory interventions, AI strengthens risk mitigation strategies and enhances the overall supply chain resilience.

Operational efficiency and high throughput

Artificial intelligence-driven automation substantially improves operational efficiency by replacing repetitive and labor-intensive tasks, including manual sampling, visual inspection, and data recording (Palakurti, 2022; van Meer *et al.*, 2025). Advanced AI-powered biosensors can detect pathogens, such as *Salmonella*, within 30 min, compared with the several days required for conventional microbiological culturing methods. This rapid analytical capability supports real-time decision-making and enhances responsiveness in high-volume and fast-moving supply chains (Ambikalekshmi *et al.*, 2025; Qian *et al.*, 2023). Such improvements highlight how AI transforms operational workflows by enabling faster, more reliable, and scalable inspection processes. The effectiveness of these systems depends on their integration into the existing production environments and on continuous calibration to maintain accuracy under varying operational conditions. Overall, AI-driven automation enhances throughput, supports real-time decision-making, and strengthens the efficiency and resilience of the food supply chain.

Non-destructive and environmentally sustainable analysis

Many AI-enabled sensing technologies, including near-infrared spectroscopy (NIRS) and HSI, enable non-destructive analysis without the need for sample destruction or the use of hazardous chemical reagents. This approach not only preserves product integrity but also reduces operational costs and environmental burdens associated with disposal of chemical waste (Arslan, 2025; Mavani *et al.*, 2021; van Meer *et al.*, 2025).

Consequently, AI-supported testing aligns with broader sustainability and environmental stewardship objectives. These approaches offer both cost-effective and environmentally sustainable alternatives to traditional testing. Their effectiveness depends on proper calibration and adaptation to different food types; yet, they provide reliable, noninvasive monitoring that preserves sample integrity while supporting timely decision-making.

Sustainability and waste reduction

Through accurate demand forecasting, inventory optimization, and shelf-life prediction, AI systems can reduce food waste by up to 30%, contributing significantly to sustainability goals within the food sector (Demiral *et al.*, 2025). These capabilities support principles of circular economy by minimizing resource losses and reducing the environmental footprint of food production and distribution (Dhal and Kar, 2025; Onyeaka *et al.*, 2024). By enabling accurate demand forecasting and proactive management, AI contributes to both environmental sustainability and resource efficiency. These capabilities reinforce the broader impact of AI, demonstrating that technological advancement can align with sustainable food production and responsible supply chain practices.

Overall, the integration of AI into food safety management delivers levels of precision, consistency, and scalability that surpass the limitations of human-dependent oversight. By shifting from reactive inspection-based approaches to predictive and preventive paradigms, AI enables early identification of contamination and spoilage risks before they compromise public health. Enhanced automation improves operational efficiency and supports real-time monitoring across complex global supply chains, while non-destructive and chemical-free analytical methods preserve product value and environmental sustainability. Collectively, these advancements contribute to the development of a more resilient, transparent, and trustworthy food system that safeguards both consumer health and industry reputation.

Disadvantages

Despite its considerable potential, the widespread adoption of AI in the food sector is constrained by a range of technical, ethical, financial, regulatory, and organizational challenges (Balta *et al.*, 2025; Wang *et al.*, 2025). Addressing these barriers is essential to ensure the responsible, effective, and equitable deployment of AI-driven food safety systems.

Technical limitations and data fragmentation

The performance and reliability of AI models are fundamentally dependent on the quality, availability, and

representativeness of the data used for training and validation. In the food industry, data are frequently fragmented, non-standardized, and, in many cases, still stored in hard-copy formats, creating significant bottlenecks for large-scale AI implementation (Dimitrakopoulou and Garre, 2025; Qian *et al.*, 2023; Tajkarimi, 2020). Moreover, AI models developed using region-specific datasets often exhibit limited generalizability when applied to different geographical contexts because of variations in climate, crop varieties, processing practices, and regulatory requirements. The opaque “black box” nature of many DL models further exacerbates these challenges, as limited interpretability can undermine trust among food safety professionals and hinder regulatory acceptance (Ambikalekshmi *et al.*, 2025; van Meer *et al.*, 2025; Yin *et al.*, 2025; Zhang *et al.*, 2025). These challenges emphasize that the effectiveness of AI in food safety is tightly coupled with robust data management practices. Ensuring high-quality, standardized, and representative datasets is essential to enhance model reliability and generalizability across diverse contexts. Addressing the interpretability of DL models is also critical, as transparent decision-making fosters trust among regulators and industry stakeholders, enabling broader adoption of AI-driven safety solutions.

Financial barriers and implementation costs

The substantial capital investment required for AI-enabled infrastructure—including high-resolution imaging systems, spectral sensors, and high-performance computing resources—represents a major barrier to adoption, particularly for SMEs and stakeholders in low- and middle-income countries (Sari *et al.*, 2025; Yin *et al.*, 2025). In many cases, the cost of AI-based inspection and quality assurance systems is estimated to be five to eight times higher than that of conventional equipment, contributing to a widening digital divide within the global food sector (Yin *et al.*, 2025). These financial challenges highlight that equitable access to AI technologies requires careful consideration of cost structures and support mechanisms. Without strategies to mitigate high implementation expenses, small-scale producers may be excluded from the benefits of AI-driven food safety, reinforcing the existing inequalities within the global supply chain. Addressing these barriers is therefore essential to ensure widespread adoption and the realization of AI's full potential in enhancing food quality and safety.

Ethical and data privacy concerns

Artificial intelligence-driven monitoring systems, especially those involving behavioral analytics, video surveillance, or facial recognition technologies, raise significant ethical concerns related to data privacy, transparency, and informed consent. There is also a risk of algorithmic bias, whereby models trained on unbalanced or skewed datasets may disproportionately classify certain regions,

producers, or demographic groups as high-risk (Arslan, 2025; Friedlander and Zoellner, 2020). Additionally, the centralized storage of sensitive supply chain and operational data increases vulnerability to cyberattacks, potentially compromising data integrity, commercial confidentiality, and public trust (Leligou *et al.*, 2024). These considerations underscore the importance of implementing AI in a responsible and transparent manner. Ensuring robust data governance, minimizing algorithmic bias, and protecting sensitive information are essential to maintain trust among stakeholders and to prevent unintended social or commercial consequences. Addressing these ethical and privacy challenges is critical for the sustainable and equitable integration of AI into food safety management systems.

Regulatory and legal uncertainty

The rapid pace of AI innovation has outstripped the development of comprehensive regulatory frameworks governing its use in food safety (Ambikalekshmi *et al.*, 2025; Ijaiya and Odumuwan, 2024). Many jurisdictions lack standardized protocols for validating AI-based tools, and critical legal questions regarding accountability and liability remain unresolved. For example, responsibility in cases where an AI system fails to detect contamination, leading to a foodborne outbreak, is often unclear. This regulatory ambiguity can foster a risk-averse “safer-not-to-know” mentality, discouraging investment and slowing institutional adoption (Alexander *et al.*, 2023; Sartoni *et al.*, 2025; Tajkarimi, 2020). These regulatory gaps highlight the need for clear standardized frameworks to guide the development, validation, and deployment of AI in food safety. Establishing transparent accountability and liability protocols is essential to foster confidence among stakeholders and encourage responsible adoption. Without such frameworks, even technically capable AI systems may face limited implementation, slowing progress toward safer and more efficient food supply chains.

Organizational resistance and skill gaps

Effective integration of AI technologies requires a multidisciplinary workforce with expertise spanning food science, data analytics, and information technology (Friedlander and Zoellner, 2020; Ikram *et al.*, 2024). However, there is a global shortage of professionals possessing this combined skill set, which limits implementation capacity across the sector (Ambikalekshmi *et al.*, 2025; Balta *et al.*, 2025). In addition, resistance from frontline workers and traditional practitioners—often driven by concerns over job displacement, constant monitoring, or loss of autonomy—can impede adoption (Demiral *et al.*, 2025; Wang *et al.*, 2025). Excessive reliance on automated systems may also lead to workforce “de-skilling,” reducing the ability of personnel to perform

manual safety checks in the event of system failures (Arslan, 2025; Sartoni *et al.*, 2025). For effective collaboration to take place between humans and AI systems, there is a need to ensure a human-in-the-loop approach, whereby AI systems are used to carry out data-driven tasks, such as real-time anomaly detection, while human experts are given ultimate responsibility for tasks, such as product recalls (Dimitrakopoulou and Garre, 2025). In order to avoid deskilling, there is a need to ensure that personnel are able to exercise “meta-autonomy” by making conscious choices about task delegation and are technically and psychologically able to take manual control during system failures. This synergy between human and AI capabilities is such that AI is able to function as a “smart agency” that is subordinated to human intelligence and is able to promote digital competencies without compromising the fundamental professional judgment required for conducting complex food safety assessments (Floridi *et al.*, 2018; Santoni de Sio and van den Hoven, 2018). As such, active human oversight is an important countermeasure to automation bias whereby human professionals are required to continually verify AI outputs through their domain expertise in food science and microbiology (Sartoni *et al.*, 2025; Singh, 2025). Addressing these challenges requires targeted training programs and change management strategies that foster trust and collaboration between human operators and AI systems. Developing multidisciplinary expertise and maintaining human oversight are critical to prevent skill erosion and ensure that AI enhances, rather than replaces, human judgment. By combining technical capability with workforce engagement, organizations can achieve more effective and sustainable integration of AI technologies into food safety operations.

Artificial intelligence offers transformative opportunities to enhance food safety, operational efficiency, and supply chain resilience. However, its successful implementation depends on addressing a complex set of interrelated challenges. These include ensuring high-quality, standardized, and representative datasets, improving model transparency and interpretability, overcoming financial and technical barriers, mitigating ethical and privacy risks, establishing clear regulatory and legal frameworks, and investing in multidisciplinary workforce development. A human-centered approach—supported by robust governance, continuous training, and cross-sector collaboration—is essential to ensure that AI technologies are deployed responsibly, equitably, and sustainably across the global food system.

To provide a structured synthesis of these technological developments, Table 1 summarizes the primary AI methodologies currently employed in food safety, highlighting their specific applications, advantages, and disadvantages.

Table 1. Summary of key AI technologies in food safety: applications, advantages, and disadvantages.

AI technology	Specific applications in food safety	Advantages	Disadvantages
Machine Learning (ML)	Pathogen detection, shelf-life prediction, and food fraud detection (adulteration)	High predictive accuracy; handles complex, nonlinear datasets	Requires large, high-quality datasets; “black box” nature (low interpretability)
Computer Vision (CV)	Automated surface inspection, sorting, real-time contaminant detection, freshness assessment	Non-destructive; high-speed processing; consistent and objective monitoring	Sensitive to lighting conditions; high initial setup costs for specialized cameras
Natural Language Processing (NLP)	Analysis of consumer reviews for foodborne illness signals; monitoring regulatory alerts	Efficient processing of unstructured text data; early warning capabilities	High linguistic complexity; risk of false positives from social media “noise.”
Internet of Things (IoT)	Real-time cold chain monitoring; smart sensors for pH and temperature tracking	Continuous data flow; enhances traceability; reduces human error in data logging	Vulnerability to cyber threats; high energy consumption; sensor calibration issues

Future Trends

The trajectory of AI in food safety and quality is advancing toward a fully integrated, autonomous, and self-correcting ecosystem, shifting the industry from reactive interventions to a “zero contamination” paradigm. Innovations in the coming years are expected to concentrate on three core areas: advanced technological integration, behavioral monitoring, and global data transparency. A particularly important development is the move from opaque “black box” DL models toward Explainable AI (XAI), which is crucial for regulatory acceptance as it allows stakeholders and inspectors to understand the reasoning behind AI-driven alerts and decision-making processes (Balta *et al.*, 2025; Sari *et al.*, 2025). Combined with edge computing, this shift enables the miniaturization of intelligent detection tools, integrating lightweight AI models into portable nanosensors that can monitor trace pollutants and pathogens in real time, dramatically reducing costs and expanding access for SMEs (Ambikalekshmi *et al.*, 2025; Yin *et al.*, 2025). The integration of IoT devices and digital twins is poised to create a planetary-scale “nervous system” for food safety. Future systems will not only continuously monitor environmental conditions, such as temperature and humidity, but also apply predictive maintenance to forecast equipment failures that could precipitate microbial outbreaks (Kowalski, 2025; Singh, 2025). The combination of blockchain with AI delivers immutable, end-to-end traceability, enabling global organizations, such as the Food and Agriculture Organization (FAO) and the World Health Organization (WHO), to assess and respond to risks across borders in a matter of seconds (Arslan, 2025; Balta *et al.*, 2025). Behavioral AI represents another transformative frontier, addressing the most unpredictable element in food safety: human behavior. Future production facilities are expected to employ unobtrusive monitoring systems capable of evaluating

hand hygiene, PPE compliance, and even workplace stress levels, which serve as early indicators of the overall safety culture. These systems can provide continuous feedback and personalized training, establishing a self-improving cycle of behavioral enhancement (Kudashkina *et al.*, 2022; Wang *et al.*, 2025). In the domain of nutrition and health, AI is anticipated to facilitate personalized dietary solutions through three-dimensional (3D) food printing and individualized nutrient profiling. By integrating biometric, genomic, and microbiome data, AI can design foods that optimize nutritional content and link food safety directly to chronic disease prevention (Bedoya *et al.*, 2022; Theodore Armand *et al.*, 2024). Additionally, the advent of quantum computing promises to extend detection capabilities, allowing for the rapid analysis of massive datasets to identify emerging zoonotic threats and chemical hazards associated with climate change (Ambikalekshmi *et al.*, 2025; Dhal and Kar, 2025).

Overall, the future of food safety probably emerges from the convergence of autonomous technological oversight and human-centered design, forming a resilient, globally connected infrastructure. By leveraging real-time data and transparent AI algorithms, the sector is positioned to move beyond traditional hazard detection toward proactive value creation, enhancing both safety and efficiency across the supply chain. From a personal perspective, these developments suggest that the next era of food safety will not only prevent contamination more effectively but also empower producers, regulators, and consumers with tools to make informed decisions, ultimately fostering a more equitable and health-conscious global food system.

Conclusions

The integration of AI and Industry 4.0 technologies is driving a profound transformation in global food

safety and quality governance. This review has shown that the shift from traditional manual oversight to interconnected, digitalized frameworks represents not merely a technological upgrade but a fundamental move toward proactive and predictive management. By replacing reactive batch testing and episodic inspections, the food sector is establishing continuous monitoring systems capable of mitigating biological, chemical, and physical hazards before they pose a risk to public health.

The core strength of this transformation lies in the combination of advanced sensing, intelligent analytics, and automated response. Technologies such as HSI, CV, and IoT-enabled biosensors provide unparalleled visibility across the supply chain. When integrated with DL algorithms and big data analytics, these tools enable the creation of digital twins and real-time early warning systems that can forecast contamination risks with high precision. Additionally, coupling AI with blockchain ensures that traceability processes occur in seconds rather than days, promoting transparency and immutable accountability from farm to fork.

Nonetheless, the path to a fully realized Food Industry 4.0 involves navigating significant technical, financial, and ethical challenges. The “black box” nature of DL models, limited standardization of datasets, and the high cost of sophisticated digital infrastructure can restrict adoption, particularly for small-scale producers. Ethical concerns around data privacy, behavioral monitoring, and algorithmic bias further emphasize that technological advancement must be accompanied by robust governance and inclusive policies.

Looking forward, innovations in Explainable AI, edge computing, and miniaturized intelligent detection devices will democratize access to advanced monitoring tools, enabling real-time assessment of trace contaminants even in resource-limited settings. The vision is a “zero-contamination” food system that integrates personalized nutrition with global-scale safety networks.

Finally, while AI offers unparalleled capabilities, human oversight remains indispensable. A human-in-the-loop approach is critical for interpreting complex data, navigating ethical dilemmas, and making high-stakes regulatory decisions. By fostering interdisciplinary collaboration among food scientists, data analysts, and policymakers, the transition to AI-driven food safety can be conducted safely, equitably, and resiliently. The successful deployment of these intelligent systems will define the next era of global food security, ensuring precision health and rigorous safety standards for all.

Highlights

- AI shifts food safety from reactive to predictive management.
- Non-destructive sensing enables real-time detection of hidden hazards.
- AI and blockchain integration ensures immutable, real-time supply chain traceability.
- Human-in-the-loop models support ethical, resilient oversight.
- Standardized datasets are essential to bridge global digital divide.

Mandatory Disclosure on Use of Artificial Intelligence

During the preparation of this work the authors used ChatGPT (OpenAI)—GPT-5.3 to assist with paraphrasing of text, grammatical corrections, and identifying and organizing references. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Competing Interests

The authors had no relevant financial interests to disclose.

Author Contributions

Both authors contributed equally to this article.

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