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REVIEW

A global perspective on artificial intelligence applications and barriers in food safety: A systematic review (2018–2025)

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Summary

Food safety remains a global priority, and the use of artificial intelligence (AI) to mitigate risks across the food supply chain has expanded rapidly. However, much of the existing literature treats AI adoption as a uniform process and pays limited attention to differences in macroeconomic contexts. This study provides a comparative analysis of AI adoption in food safety between high-income countries (HICs) and low- and middle-income countries (LMICs), focusing on application areas, key actors, and implementation challenges. A systematic literature review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Sixty-five empirical studies published between 2018 and 2025 were identified from Scopus (Elsevier, Amsterdam, Netherlands), Web of Science (Clarivate Analytics, Philadelphia, USA), and Google Scholar (Google, Mountain View, California, USA). The findings show clear structural differences in AI utilisation. In HICs, AI strengthens mature food safety systems, supports regulatory compliance, and facilitates predictive risk management. In LMICs, AI is mainly applied to basic screening, operational risk control, and traceability, but adoption is constrained by limited data availability, weak digital infrastructure, and insufficient technical capacity. Overall, AI adoption reflects institutional maturity and systemic capacity rather than technological capability alone, highlighting the need for context-specific implementation strategies.

Keywords

food safety; artificial intelligence; systematic literature review; high-income countries; low-and middle-income countries; technology adoption; regulatory challenges

Ensuring a safe and nutritious food supply is critical for consumer health, human capital development, and national resilience, making it a persistent global priority for governments, industry, and academia [1]. Expanding markets and rising consumer demand have spurred innovative approaches to verify compliance with food standards [2]. Nevertheless, substantial risks persist, including foodborne illnesses, malnutrition, and diet-related mortality. Additionally, while food fraud is rarely directly harmful [3], it imposes severe economic and public health burdens [2].

To mitigate these risks, advances in machine learning, computer vision, and sensor technology have accelerated the integration of artificial intelligence (AI) into food safety management. AI assists regulators and industry stakeholders in monitoring raw materials and overseeing highly vulnerable processing and packaging stages [1]. Because consumers cannot independently detect contaminants or verify product origins, AI-enabled traceability systems provide essential end-to-end supply chain visibility [4]. Throughout production, processing, transport, and retail, digital sensors generate massive datasets. Applying AI and big data analytics to this information improves risk detection, real-time monitoring, and predictive decision-making [5, 6], allowing earlier and more effective mitigation of contamination, fraud, and operational failures.

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Despite this potential, AI adoption in food safety remains globally uneven. The emergent state of AI highlights the need to understand implementation disparities, particularly between high-income countries (HICs) and low- and middle-income countries (LMICs). HICs increasingly leverage AI for quality monitoring, hazard detection, and regulatory compliance [4, 7–9]. Conversely, LMICs face persistent adoption barriers, including restricted technology access, financial constraints, inadequate digital infrastructure, weak regulatory frameworks, and skill shortages [6, 10–12]. Bridging these technological gaps to improve global food safety requires targeted research and context-specific strategies.

Existing systematic reviews document the growing research on AI in food safety, particularly regarding contamination detection, quality inspection, and traceability [13, 14]. However, they often treat AI adoption as a uniform technological trend, largely overlooking variations across economic and institutional contexts. In reality, data generation capacity, digital infrastructure, and regulatory enforcement differ substantially between HICs and LMICs [15, 16]. These structural differences likely dictate not only the extent of AI adoption but also the operational objectives, key stakeholders, and constraints within local food safety systems.

Addressing this gap, this study systematically compares AI adoption in food safety between HICs and LMICs. By evaluating specific applications, primary actors, and prevailing implementation barriers, we investigate how institutional capacity, data environments, and resource constraints shape AI functionality in food safety governance. Ultimately, this comparative analysis provides the empirical foundation necessary to develop context-sensitive frameworks, guiding future research and equitable policy formulation across diverse economic landscapes.

MATERIALS AND METHODS

Study design

Although AI is widely used across various sectors, research specifically addressing its application in food safety remains limited [17]. Existing literature often discusses AI in food safety only indirectly, typically within broader agricultural or manufacturing contexts. To address this gap, this study employs a systematic literature review to identify, consolidate, and critically analyse the empirical research on AI in food safety.

To ensure methodological transparency and rigor, the review adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The process involved five stages: study identification, screening, eligibility assessment, data extraction, and data synthesis. The analysis was guided by the following research questions:

- RQ1: What functional roles does AI play in food safety?
- RQ2: Which actors are involved in AI implementation, and how does their involvement vary across economic contexts?
- RQ3: What challenges constrain AI adoption, and how do these challenges differ between HICs and LMICs?

Step 1: Study identification

A comprehensive literature search was conducted using three databases: Scopus (Elsevier, Amsterdam, Netherlands), Web of Science (Clarivate Analytics, Philadelphia, Pennsylvania, USA), and Google Scholar (Google, Mountain View, California, USA), to ensure broad coverage across disciplines. Given the large volume of records and the relevance-based ranking system of Google Scholar, screening was limited to the first 100 pages (approximately 1 000 records). This approach is common in systematic reviews

Tab. 1. Search strings for literature selection.

Database	Search strings
Scopus	TITLE-ABS-KEY(“artificial intelligence”) AND TITLE-ABS-KEY(“food safety”) AND (TITLE-ABS-KEY(“machine learning”) OR TITLE-ABS-KEY(“deep learning”)) AND (TITLE-ABS-KEY(“food supply chain”) OR TITLE-ABS-KEY(distribution) OR TITLE-ABS-KEY(manufacturing) OR TITLE-ABS-KEY(“post-market”)) AND (TITLE-ABS-KEY(barriers) OR TITLE-ABS-KEY(challenges) OR TITLE-ABS-KEY(implementation))
Web of Science	TS=(“artificial intelligence”) AND TS=(“food safety”) AND TS=(“machine learning” OR “deep learning”) AND TS=(“food supply chain” OR distribution OR manufacturing OR “post-market”) AND TS=(barriers OR challenges OR implementation)
Google Scholar	“artificial intelligence” AND “food safety” AND (“machine learning” OR “deep learning”) AND (“food supply chain” OR distribution OR manufacturing OR “post-market”) AND (barriers OR challenges OR implementation)

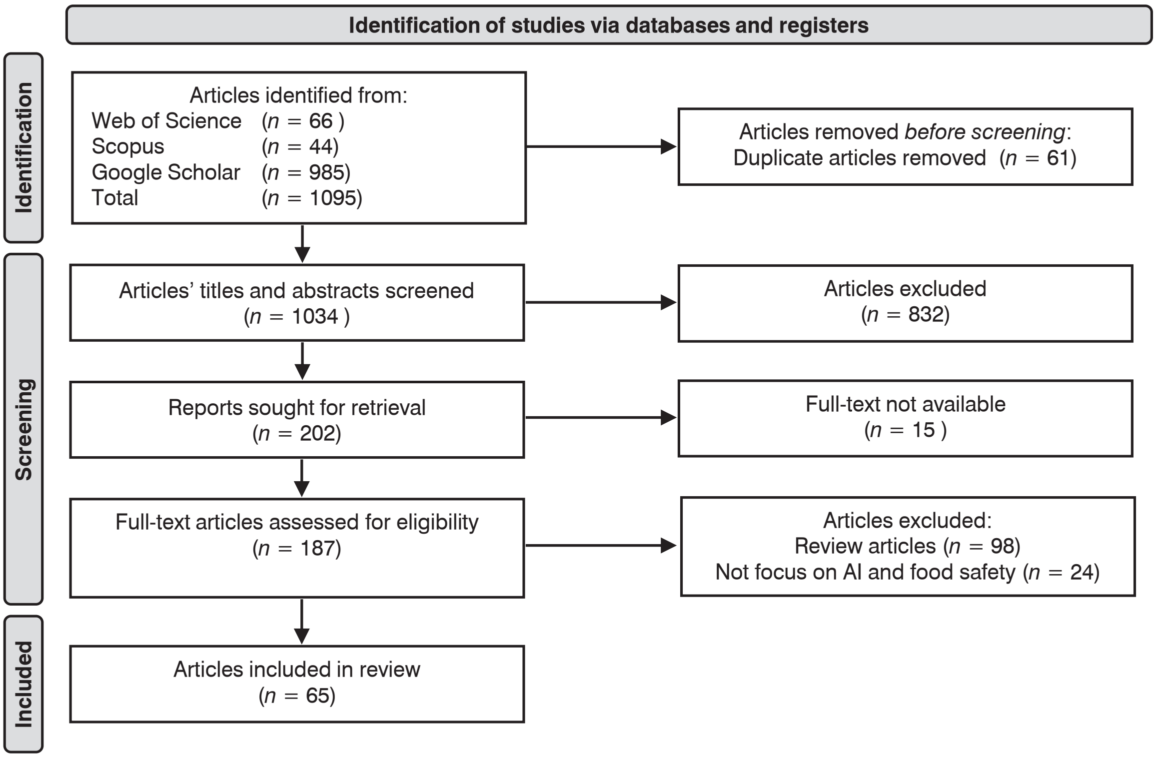

Fig. 1. PRISMA flow diagram.

to maintain feasibility while capturing the most relevant literature [18].

The search strategy combined keywords related to AI and food safety. The core string included: ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("food safety") AND ("food supply chain" OR distribution OR manufacturing OR "post-market") AND (barriers OR challenges OR implementation). Database-specific syntax was applied (Tab. 1). The searches, conducted on 17 November 2025, were restricted to publications from 2016 to 2025 to capture recent AI advancements in the field. Where applicable, searches were limited to titles, abstracts, and keywords. All retrieved records were exported for screening; the overall selection process is detailed in the PRISMA flow diagram (Fig. 1).

Step 2: Screening process

The initial search yielded 1 095 records (Web of Science: 66; Scopus: 44; Google Scholar: 985). These were imported into Rayyan (Rayyan, Cambridge, Massachusetts, USA), a systematic review management tool, for duplicate removal and blinded screening. After removing 61 duplicates, four reviewers independently screened the remaining 1 034 titles and abstracts against predefined inclusion and exclusion criteria. Disagreements were resolved through consensus. Studies with ambiguous eligibility were retained for full-text assessment. Ultimately, 832 records were excluded at this stage, leaving the selected articles for full-text evaluation.

Step 3: Eligibility assessment

Of the 202 records selected for full-text assessment, 15 could not be retrieved. The remaining full-text articles were rigorously evaluated against the inclusion and exclusion criteria to determine final eligibility.

Studies were included if they: (1) were peer-reviewed and published between 2016 and 2025; (2) focused explicitly on AI applications in food safety; (3) reported risks, limitations, or implementation challenges; (4) presented empirical findings; and (5) provided a clear geographical context and/or identifiable actor level.

Conversely, studies were excluded if they were: (1) non-peer-reviewed materials (e.g., theses, reports, opinion pieces); (2) review-based publications (e.g., systematic reviews, bibliometric analyses); (3) not written in English; (4) unavailable in full text; or (5) not primarily concerned with AI and food safety.

Following full-text evaluation, 122 articles were excluded, primarily review-based studies (n = 98) and those lacking a direct focus on AI in food safety (n = 24). The final sample comprised 65 empirical studies.

Step 4: Data extraction

To ensure consistency, a structured data extraction form was utilised. Extracted bibliographic information included authorship, publication year and type, the first author's affiliated country, and the country's economic classification (HIC or LMIC). Analytical variables captured the research focus, primary AI users (e.g., farmers, industry, government, or multi-actor arrangements), AI application types, and reported implementation challenges. Reviewers manually extracted and cross-checked all data to guarantee accuracy and reliability.

Step 5: Data synthesis

Data synthesis utilised thematic analysis and comparative descriptive methods, guided by the motivation–implementation–actor–challenge (MIAC) analytical framework (Fig. 2). This process occurred in four stages. First, descriptive mapping of the study distribution across HICs and LMICs. Second, categorisation of AI applications by their primary functional focus (e.g., risk assessment, contamination detection, fraud detection, traceability, and quality monitoring). Third, identification of implementing actors, grouping them into major categories (e.g., industry, regulators, and upstream supply-chain actors). Fourth, inductive coding of reported challenges, organising them into thematic categories based on recurring patterns. Finally, a comparative analysis between HICs and LMICs was conducted to highlight differences in application focus, actor involvement, and implementation constraints. Rather than viewing cross-country variations in AI adoption as isolated technological choices, this approach interprets them as outcomes shaped by broader structural and institutional conditions [19].

RESULTS

Geographical distribution

Although the literature search spanned 2016 to 2025, all included primary studies were published between 2018 and 2025. Publication activity increased sharply after 2020, with 95 % of the included studies published between 2020 and 2025. Of the 202 full-text articles screened, 65 met the eligibility criteria. Based on first-author affiliations, HICs produced a slightly larger share of the publications (54 %, n = 35) than LMICs (46 %, n = 30).

Respectively, HICs were represented by North America (USA n = 8, Canada n = 1), Europe (Italy n = 4, United Kingdom n = 4, other European countries n = 11), Asia (n = 4), and Australia (n = 3). Meanwhile, LMICs were dominated by Asia (China including Taiwan n = 13, India n = 12, others n = 4), with only one study from Africa (Nigeria). Publication years spanned 2018–2025, of which 95 % were published after 2020.

At the country level, China (n = 13), India (n = 12), and USA (n = 8) were the most prolific contributors. Their dominance in this field aligns with broader global trends: according to 2023 Scimago rankings, these three populous nations lead scientific output in both food science and artificial intelligence. Furthermore, they are

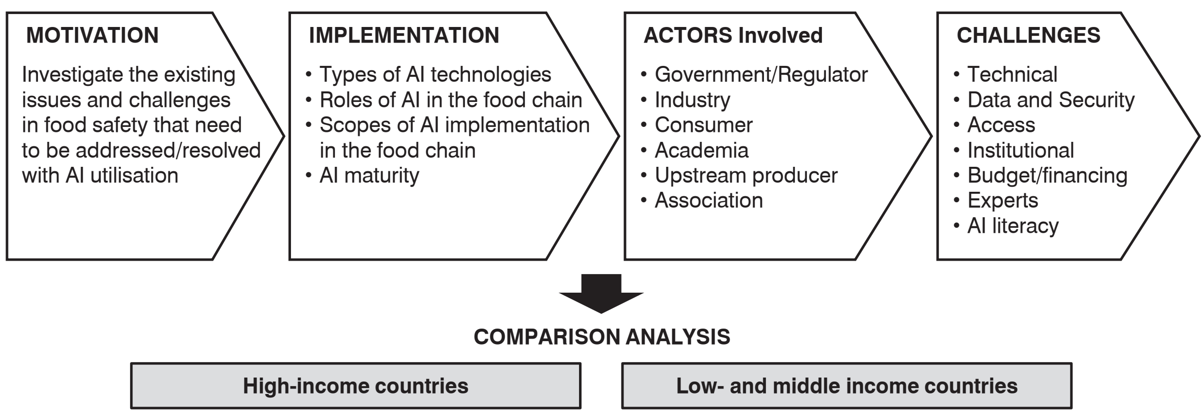

Fig. 2. Motivation-implementation-actors-challenges (MIAC) analytical framework.

major agricultural producers. According to 2022 FAO data, China ranks first globally in agricultural output ($1\,620 \times 10^9$ USD), followed by India (524.1×10^9 USD) and USA (474.2×10^9 USD). Technologically, the AI Index 2024 Annual Report highlights USA as the leader in developing AI models (61 models), while China dominates AI patent activity, accounting for 61.1 % of global AI patent origins.

High-income countries

Application of AI in food safety

In HICs, research primarily focuses on AI applications for risk assessment, regulatory surveillance, and early warning systems. Regulators and auditors frequently deploy AI to manage large datasets, such as prioritising hazards among thousands of Rapid Alert System for Food and Feed (RASFF, European Commission, Brussels, Belgium) notifications [20] or predicting food recalls caused by contamination and allergen mislabelling [9, 21]. Authentication and origin verification also represent a significant focus area. For instance, digital scanning techniques achieved 98.4% accuracy in identifying the botanical origin of honey, reducing analysis time from approximately 30 min to mere seconds [22]. Similarly, supervised learning models (e.g., XGBoost) accurately identified the geographical origin of mozzarella di bufala protected designation of origin (PDO) products (accuracy: 0.825 ± 0.032) [23].

Furthermore, contamination and pathogen detection feature prominently in HIC literature. A Japanese study reported that machine learning algorithms reduced pathogen identification time from 24 h to 10 h while achieving 96% accuracy [24]. Another study demonstrated that convolutional neural network (CNN) architectures provided faster, more cost-effective melamine detection in coffee capsules compared to conventional chemical testing [25]. Collectively, these studies illustrate AI's capacity to enhance regulatory efficiency, verify food authenticity, and accelerate hazard detection across diverse food categories in HICs.

Implementing actors

In HICs, robust digital infrastructure and high regulatory capacity enable industrial actors and regulatory authorities to drive AI adoption in food safety. Food manufacturers and processors are the primary AI users, representing the majority of the reviewed studies. These stakeholders frequently embed AI systems within integrated production and processing environments to detect contamination risks and process deviations before they escalate into systemic food safety incidents. Empirical evidence highlights the use of machine learning for microbial anomaly detection in dairy production, alongside CNN-based systems for automated inspections (e.g., expiry date verification), thereby facilitating preventive, data-driven safety management [26, 27].

Regulatory authorities form the second major user group. National and supranational agencies increasingly deploy AI for automated risk classification, surveillance, and compliance monitoring, utilising data from inspections, laboratories, import controls, and post-market tracking. By integrating AI-based traceability and detection tools into their oversight frameworks, these agencies enhance real-time monitoring and early warning capabilities [28]. For example, applying machine learning techniques to RASFF data has successfully identified high-risk products, hazards, and trade patterns, ultimately improving inspection prioritisation and regulatory decision-making [29].

Challenges

Lack of model interpretability is a primary challenge in HICs ($n = 7$), particularly for regulatory applications that demand transparency and explainability. While deep learning and transformer-based models achieve high predictive accuracy, they often fail to provide clear justifications for risk classifications, thereby limiting regulatory acceptance [30]. This is especially evident in AI-based analyses of RASFF notifications, where ambiguous textual descriptions, class imbalances, and computational complexity hinder interpretability [30]. Small dataset sizes and data insufficiency further exacerbate these issues, reducing both reliability and explainability [31–34].

Model generalisation and overfitting constitute another recurring challenge ($n = 6$). AI models trained on specific products or environments often underperform when applied to novel contexts. Industry evidence indicates that environmental variability, sensor noise, manual data-entry errors in enterprise resource planning (ERP) systems, and incomplete supervisory control and data acquisition (SCADA) records increase overfitting risks and compromise predictive robustness [35].

Several studies also report difficulties in distinguishing meaningful food safety signals from noise within large, heterogeneous datasets ($n = 5$). Weak temporal correlations, shallow datasets, and complex variable interactions often undermine model accuracy [9, 21]. Similarly, image-based inspection systems struggle with bacterial colony misidentification caused by air bubbles or food particles, reducing their reliability under real-world conditions [24, 30].

Data privacy and regulatory constraints further limit AI adoption ($n = 5$). Privacy regulations, proprietary data concerns, and interoperability barriers restrict cross-firm and cross-border data sharing, ultimately constraining model training and scalability [18, 36, 37]. Furthermore, despite advanced digital infrastructures, legacy systems remain a persistent obstacle ($n = 2$). Many facilities rely on outdated hardware and software that resist integration with modern AI and cloud-based solutions [30]. Consequently, system upgrades are costly and time-consuming, particularly within complex multinational supply chains [38].

Low-middle-income countries

Artificial intelligence application

In LMICs, structural weaknesses in inspection capacity, data availability, and supply-chain transparency continue to constrain food safety governance. Consequently, most studies focus on AI applications for food adulteration and fraud detection, reflecting persistent challenges with product authenticity and informal market structures. AI techniques are commonly deployed to detect adulterants in high-value products (e.g., saffron, chilli powder, and pistachios) and illegal additives (e.g., ractopamine). These approaches frequently combine machine learning with low-cost, non-destructive analytical or imaging methods to achieve high detection accuracy while reducing the time and cost associated with conventional laboratory analyses [39–41].

Beyond fraud detection, AI is applied to monitor contamination and pathogens, including pesticide residues in vegetables, heavy metals in soil and grains, and microbial spoilage in meat. Image-based systems and hybrid Bayesian models facilitate early risk detection under data-constrained conditions [42–44]. AI-driven traceability applications are also increasingly reported; notably, blockchain-enabled tracking systems and machine-learning analyses of transaction data help identify suspicious trading patterns and prevent fraud [45, 46]. A smaller subset of studies examines IoT-based real-time sensing for spoilage monitoring and automated sorting. In these cases, vision-based systems reduce labour dependence and enable continuous operations in resource-limited environments [47–49].

Implementing actors

Industry actors and producers are the primary users of AI for food safety in LMICs ($n = 20$). Food processors, traders, and small-to-medium-sized manufacturers apply AI to detect adulteration, monitor contamination, and automate inspections, particularly for high-risk and high-value products like spices, meat, and grains [39, 40, 44].

Farmers and upstream supply-chain actors form the second key user group ($n = 12$), featuring prominently in studies addressing pesticide residues, soil contamination, spoilage monitoring, and post-harvest quality management. For these users, AI-enabled sensing and image-based systems support early risk detection and mitigate losses under resource-constrained farming conditions [42, 43, 47].

Challenges

Across LMIC studies, limited data availability and quality emerge as the most frequently reported challenges ($n = 9$). Incomplete and poorly digitised food safety records, limited regulatory coverage, and fragmented transaction data severely constrain model training and reliability [46, 50]. Additional issues, such as class imbalance, the underrepresentation of high-risk cases, and a shortage of high-quality labelled data, bias model performance and reduce predictive accuracy [42, 51, 52].

The absence of standardised data formats for certification and sustainability information further complicates cross-chain data integration [53]. Furthermore, models developed under controlled experimental conditions exhibit limited generalisability when deployed in real-world environments characterised by high noise levels and operational variability [54, 55]. High-dimensional datasets with redundant features also increase overfitting risks, diminishing model robustness [49].

Infrastructure and resource constraints represent the second major barrier to AI adoption in LMICs ($n = 7$). Advanced AI systems require high-performance computing, stable connectivity, and specialised hardware – resources that are frequently unavailable or unaffordable [48, 54, 55]. Costs extend beyond initial investments to encompass software development, system integration, personnel training, and ongoing maintenance, posing significant barriers for resource-constrained small and medium enterprises [53, 56].

Shortages of machine learning expertise and technically trained personnel also limit the operational sustainability of these systems across industry and regulatory institutions [40]. Practical challenges, such as unstable networks and high maintenance demands, inflate operational costs and reduce real-world feasibility [57]. Collectively, these constraints indicate that despite promising pilot outcomes, the scalability and long-term adop-

Tab. 2. Comparison of artificial intelligence utilisation between high-income countries and low- and middle-income countries.

Dimension analysis	High-income countries		Low- and middle-income countries	
	Utilisation	*n*	Utilisation	*n*
Motivation to utilise AI	Operating formal supply chains		Informal supply chain and fragmented markets	
	Open data availability, data accessibility and high standard data quality		Limited data availability	
	Mature regulatory systems		High prevalence of adulteration	
	Strong institutional enforcement		High prevalence contamination toward food-borne diseases	
Primary focus of AI use	Regulatory surveillance		Fraud detection	
	Compliance monitoring		Contamination screening	
	System optimisation		Loss reduction	
	Preventive risk management		Operational monitoring	
Implementation AI in food safety	Risk assessment and regulatory alerts	11	Adulteration and food fraud detection	12
	Authentication and origin verification	10	Traceability and monitoring along supply chain	9
	Contamination and pathogen detection	10	Contamination and pathogen detection	11
	Prediction of spoilage and shelf-life	8	Monitoring of food spoilage	6
Actors involved	Industry and food manufacturers	17	Industry actors and processors	20
	Food safety regulators	14	Farmers and upstream producers	12
Challenges	Lack of interpretability for regulatory decision-making	7	Data availability and data quality	9
	Generalization and overfitting	6	Infrastructure and resource constraints	7
	Noise in large and complex datasets	5	Complexity of AI system and integration with other technologies	6
	Data privacy and general data protection regulation constraints	5		
	Integration between old and new system	2		

n – number of studies within each income group reporting the specified artificial intelligence utilisation (one study may contribute to multiple categories).

tion of AI in LMIC food safety systems heavily depend on financial, technical, and infrastructural capacity.

System complexity and integration challenges are reported in a smaller subset of studies ($n = 6$). These challenges stem from the operational burden of deploying multi-component architectures (e.g., integrated IoT–blockchain–analytics systems) and the computational demands that hinder real-time deployment and scalability. Fragmented and decentralised supply chains further complicate implementation by necessitating complex coordination across multiple actors and data systems [50]. Several studies note that advanced frameworks often require simplification or redesign to enable edge or real-time deployment, whereas large-scale infrastructures can introduce inefficiencies and security risks [40, 55, 56]. Overall, system complexity remains a significant constraint on the operational feasibility of integrated AI solutions in LMICs.

DISCUSSION

The findings indicate that institutional capacity is a primary factor shaping differences in AI utilisation for food safety across income groups (Tab. 2). In LMICs, persistent structural weaknesses in food safety governance direct AI use toward mitigating immediate risks associated with foodborne diseases, contamination, and adulteration. Consequently, applications in these contexts focus on rapid screening, traceability, and fraud detection, primarily to help producers and industry actors comply with fundamental food safety regulations.

In contrast, HICs operate within well-established institutional frameworks characterised by robust regulation, enforcement mechanisms, and compliance systems. Here, AI is increasingly used to optimise existing operations rather than address foundational governance gaps. HIC studies emphasise deploying advanced AI models to enhance system efficiency, integrate large-scale data streams, and anticipate emerging risks. This forward-looking orientation reflects a transition from reactive risk management to predictive and preventive governance, driven by next-generation AI technologies.

These institutional differences also manifest in the implementation challenges experienced across income groups. In LMICs, fundamental barriers, such as limited data availability, poor data quality, inadequate digital infrastructure, and a shortage of skilled personnel, constrain AI adoption. These deficits complicate the deployment and long-term sustainability of AI systems within existing frameworks. Conversely, HIC challenges primarily involve refining model performance and addressing ethical or governance concerns related to responsible AI deployment. Specific issues include managing data noise and complexity, improving model generalisation, integrating AI with legacy systems, ensuring data privacy, and embedding AI outputs into transparent regulatory decision-making processes.

The governance-related challenges identified in this review align closely with broader discourse on trustworthy and responsible AI. Principles such as interpretability, transparency, data protection, and accountability are recognised as essential for ethical AI deployment [58]. In regulatory domains like food safety, explainable and auditable models are particularly critical because AI-driven decisions directly impact public health outcomes and market access. This emphasis on explainability aligns with international efforts, such as the Defense Advanced Research Projects Agency (DARPA, Arlington, Virginia, USA) Explainable AI programme [59], to promote transparent algorithmic decision-making [60], highlighting the need to balance technical performance with institutional and governance capacity.

Finally, the broader scope and complexity of AI applications in HICs reflect greater food safety awareness and long-term strategic investments. In these regions, funding AI infrastructure is viewed as a future-oriented strategy, enhancing economic competitiveness, labour productivity, and product quality, rather than a financial burden. Conversely, because institutional capacity remains a foundational constraint in LMICs, AI is primarily adopted to enforce basic compliance across the fresh and processed food sectors. This demonstrates the necessity of resolving fundamental governance and enforcement gaps before pursuing advanced optimisation strategies.

Research limitations

Several limitations warrant consideration when interpreting these findings. First, many included studies evaluate prototype or laboratory-scale AI models developed under controlled conditions. These models likely overestimate real-world performance, particularly in operational environments hindered by poor data quality and limited system integration. Furthermore, methodological constraints, such as small sample sizes, class imbalances, and insufficient external validation, were frequently reported, especially within LMIC-focused research.

Second, the evidence base is geographically concentrated, predominantly featuring studies from China, India, USA, and select European nations. This limits the generalisability of the observed patterns to regions with differing institutional and economic contexts. Finally, a publication bias favouring technically successful applications likely obscures failed implementations and practical operational barriers.

CONCLUSIONS

This review demonstrates that disparities in artificial intelligence (AI) adoption for food safety between HICs and LMICs stem primarily from differences in institutional maturity rather than technological access alone. Governance structures and baseline food safety awareness dictate the motivations, application types, and key actors driving AI integration. Restricted by institutional constraints, LMICs predominantly apply AI to achieve basic regulatory compliance and mitigate immediate risks. Conversely, robust regulatory frameworks in HICs enable stakeholders to leverage AI for system optimisation, predictive risk management, and proactive hazard anticipation.

This study advances existing literature [13, 14] by proposing a unified analytical framework that evaluates AI adoption across four dimensions: motivation, implementation focus, actor involvement, and operational challenges. By applying geographical and income-based clustering, the analysis clarifies how institutional capacity dictates technological trajectories. Specifically, it highlights a distinct transition: as food safety systems mature, AI utilization shifts from foundational risk control to advanced disease prevention and quality enhancement.

Accelerating effective AI integration in LMICs requires substantial improvements in institutional capacity. Strategic priorities include strengthening regulatory enforcement, upgrading data infrastructure, bridging the technical skills gap, and fostering cross-sector collaboration among government, industry, and academia. Furthermore, translating technological potential into sustainable improvements requires transitioning from isolated pilot studies to full-scale, practical applications. Future research should build upon this framework by empirically evaluating the long-term impact of AI on food safety outcomes across diverse economic contexts.

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REFERENCES

1. Mu, W. – Kleter, G. – Bouzembrag, Y. – Dupuoy, Y. – Frewer, L. – Radwan, A. N. F. – Marvin, H.: Making food systems more resilient to food safety risks by including artificial intelligence, big data, and internet of things into food safety early warning and emerging risk identification tools. Comprehensive Review in Food Science and Food Safety, *23*, 2024, article e16296. DOI: 10.1111/1541-4337.13296.
2. Bagnulo, E. – Strocchi, G. – Bicchi, C. – Liberto, E.: Industrial food quality and consumer choice: Artificial intelligence-based tools in the chemistry of sensory notes in comfort foods (coffee, cocoa and tea). Trends in Food Science and Technology, *147*, 2024, article 104415. DOI: 10.1016/j.tifs.2024.104415.
3. Manning, L. – Soon, J. M.: Food safety, food fraud, and food defense: a fast evolving literature. Journal of Food Science, *81*, 2016, pp. R823–R834. DOI: 10.1111/1750-3841.13256.
4. Wang, Y. – Wu, J. – Deng, H. – Zeng, X.: Food image recognition and food safety detection method based on deep learning. Computational Intelligence and Neuroscience, *2021*, 2021, article 1268453. DOI: 10.1155/2021/1268453.
5. Karanth, S. – Benefo, E. O. – Patra, D. – Pradhan, A. K.: Importance of artificial intelligence in evaluating climate change and food safety risk. Journal of Agricultural and Food Research, *11*, 2023, article 100485. DOI: 10.1016/j.jafr.2022.100485.
6. Zhou, Q. – Zhang, H. – Wang, S.: Artificial intelligence, big data, and blockchain in food safety. International Journal of Food Engineering, *18*, 2022, article 0299. DOI: 10.1515/ijfe-2021-0299.
7. Feng, Y. – Wang, Y. – Beykal, B. – Qiao, M. – Xiao, Z. – Luo, Y.: A mechanistic review on machine learning-supported detection and analysis of volatile organic compounds for food quality and safety. Trends in Food Science and Technology, *143*, 2024, article 104297. DOI: 10.1016/j.tifs.2023.104297.
8. Nogales, A. – Díaz-Morón, R. – García-Tejedor, A. J.: A comparison of neural and non-neural machine learning models for food safety risk prediction with European Union RASFF data. Food Control, *134*, 2022, article 108697. DOI: 10.1016/j.foodcont.2021.108697.
9. Makridis, G. – Mavrepis, P. – Kyriazis, D.: A deep learning approach using natural language processing and time-series forecasting towards enhanced food safety. Machine Learning, *112*, 2023, pp. 1287–1313. DOI: 10.1007/s10994-022-06151-6.
10. Abass, T. – Itua, E. O. – Bature, T. – Eruaga, M. A.: Innovative approaches to food quality control: AI and machine learning for predictive analysis. World Journal of Advanced Research and Reviews, *21*, 2024, pp. 823–828. DOI: 10.30574/wjarr.2024.21.3.0719.
11. Chhetri, K. B.: Applications of artificial intelligence and machine learning in food quality control and safety assessment. Food Engineering Reviews, *16*, 2024, pp. 1–21. DOI: 10.1007/s12393-023-09363-1.
12. Akdoğan, E. – Baş, D.: Promising tools for food safety and quality: artificial intelligence and smartphones. Journal of Food Health and Technology Innovations, *5*, 2022, pp. 368–375. ISSN: 2667-5803.
13. Wang, X. – Bouzembrak, Y. – Lansink, A. G. J. M. O. – Fels-Klerx, H. J. V. D.: Application of machine learning to the monitoring and prediction of food safety: A review. Comprehensive Reviews in Food Science and Food Safety, *21*, 2022, pp. 416–434. DOI: 10.1111/1541-4337.12868.
14. Liu, Z. – Wang, S. – Zhang, Y. – Feng, Y. – Liu, J. – Zhu, H.: Artificial intelligence in food safety: a decade review and bibliometric analysis. Foods, *12*, 2023, article 1242. DOI: 10.3390/foods12061242.
15. Khan, M. S. – Umer, H. – Faruqe, F.: Artificial intelligence for low income countries. Humanities & Social Sciences Communications, *11*, 2024, article 1422. DOI: 10.1057/s41599-024-03947-w.
16. Chen, H. – Zeng, D. – Qin, Y. – Fan, Z. – Ci, F. N. Y. – Klonoff, D. C. – Ji, J. S. – Zhang, S. – Amissah Arthur, K. N. – Jiménez de Tavárez, M. M. – Masood, S. – Le, P. V. – Keane, P. A. – Sheng, B. – Wong, T. Y. – Tham, Y. C.: Large language models and global health equity: a roadmap for equitable adoption in LMICs. The Lancet Regional Health – Western Pacific, *63*, 2025, article 101707. DOI: 10.1016/j.lanwpc.2025.101707.
17. Chen, T. C. – Yu, S. Y.: Research on food safety sampling inspection system based on deep learning. Food Science and Technology, *42*, 2022, article 29121. DOI: 10.1590/fst.29121.
18. Miake-Lye, I. M. – Mak, S. – Begashaw, M. M. – Shekelle, P. G.: Using Google to search for evidence: how much is enough? One center's experience. Systematic Reviews, *14*, 2025, article 92. DOI: 10.1186/s13643-025-02836-w.
19. Thakur, S.: AI readiness across nations: a panel analysis of policy, governance, and innovation factors. International Journal for Multidisciplinary Research, *7*, 2025. ISSN: 2582-2160. DOI: 10.36948/ijfmr.2025.v07i03.44028.
20. Talari, G. – Nag, R. – O'Brien, J. – McNamara, C. –

Cummins, E.: A data-driven approach for prioritising microbial and chemical hazards associated with dairy products using open-source databases. Science of the Total Environment, *908*, 2024, article 168456. DOI: 10.1016/j.scitotenv.2023.168456.

21. Makridis, G. – Mavrepis, P. – Kyriazis, D. – Polychronou, I. – Kaloudis, S.: Enhanced food safety through deep learning for food recalls prediction. In: Appice, A. – Tsoumakas, G. – Manolopoulos, Y. – Matwin, S. (Eds): Discovery Science, DS 2020, Lecture Notes in Computer Science, vol- *12323.* Cham : Springer, 2020, pp. 566–580. DOI: 10.1007/978-3-030-61527-7_37.
22. Banach, J. K. – Rujna, P. – Lewandowski, B.: Integrated process-oriented approach for digital authentication of honey in food quality and safety systems – a case study from a research and development project. Applied Sciences, *15*, 2025, article 7850. DOI: 10.3390/app15147850.
23. Magarelli, M. – Di Bitonto, P. – De Filippis, F. – Novielli, P. – Magliulo, R. – Diacono, D. – Bellotti, R. – Tangaro, S.: Securing origin integrity through machine learning analysis of mozzarella di Bufala PDO microbiome. In: 2024 IEEE International Workshop on Metrology for Industry 4.0 and IoT (MetroInd4.0 and IoT 2024 Proceedings). New York : IEEE, 2024, pp. 38–42. ISBN:979-8-3503-8582-3. DOI: 10.1109/MetroInd4.0IoT61288.2024.10584209.
24. Tago, H. – Maeda, Y. – Tanaka, Y. – Kohketsu, H. – Lim, T. – Harada, M. – Yoshino, T. – Matsunaga, T. – Tanaka, T.: Line image sensor-based colony fingerprinting system for rapid pathogenic bacteria identification. Biosensors and Bioelectronics, *249*, 2024, article 116006. DOI: 10.1016/j.bios.2024.116006.
25. Hernansanz-Luque, N. – Pérez-Calabuig, A. M. – Pradana-López, S. – Cancilla, J. C. – Torrecilla, J. S.: Real-time screening of melamine in coffee capsules using infrared thermography and deep learning. Journal of Food Engineering, *402*, 2025, article 112675. DOI: 10.1016/j.jfoodeng.2025.112675.
26. Beck, K. L. – Haiminen, N. – Agarwal, A. – Carrieri, A. P. – Madgwick, M. – Kelly, J. – Pylro, V. – Kawas, B. – Wiedmann, M. – Ganda, E.: Development and evaluation of statistical and artificial intelligence approaches with microbial shotgun metagenomics data as an untargeted screening tool for use in food production. mSystems, *9*, 2024, article e00840-24. DOI: 10.1128/msystems.00840-24.
27. Kollia, I. – Stevenson, J. – Kollias, S.: AI-enabled efficient and safe food supply chain. Electronics, *10*, 2021, article 1223. DOI: 10.3390/electronics10111223.
28. Zhang, W. – Chen, E. – Anderson, M. – Thompson, S. – Lee, J.: Multimodal deep learning-based intelligent food safety detection and traceability system. International Journal of Management Science Research, *8*, 2025, pp. 71–76. DOI: 10.53469/ijomsr.2025.08(03).09.
29. Sari, O. F. – Amer, E. – Bader-El-Den, M. – Ince, V. – Leadley, C.: AI-driven risk assessment in food safety using EU RASFF database. Food and Bioprocess Technology, *18*, 2025, pp. 6282–6303. DOI: 10.1007/s11947-025-03819-4.
30. Gaye, A. – Paflo, B. N. – Donkor, A. A.: Evaluating the effectiveness of AI-driven anomaly detection in food safety compliance monitoring. International Journal of Frontline Research in Life Sciences, *3*, 2025, pp. 1–9. DOI: 10.56355/ijfrls.2025.3.2.0022.
31. Teklemariam, T. A.: Raman and mid-infrared spectroscopy coupled with machine–deep learning for adulterant detection in ground turmeric. Applied Spectroscopy Practica, *2*, 2024, pp. 1–19. DOI: 10.1177/27551857241250014.
32. Weller, D. L. – Love, T. M. T. – Wiedmann, M.: Interpretability versus accuracy: a comparison of machine learning models built using different algorithms, performance measures, and features to predict *E. coli* levels in agricultural water. Frontiers in Artificial Intelligence, *4*, 2021, article 628441. DOI: 10.3389/frai.2021.628441.
33. Wu, P.-Y. – Chou, W.-C- – Wu, X. – Kamineni, V. N. – Kuchimanchi, Y. – Tell, L. A. – Maunsell, F. P. – Lin, Z.: Development of machine learning-based quantitative structure–activity relationship models for predicting plasma half-lives of drugs in six common food animal species. Toxicological Sciences, *203*, 2024, pp. 52–66. DOI: 10.1093/toxsci/kfae125.
34. Rose, E. – Lee, S. – Young, P.: Early detection of food safety hazards in global supply chains using predictive analytics. Frontiers in Biotechnology and Genetics, *2*, 2025, pp. 1–8. DOI: 10.71465/fbg278.
35. Rakholia, R. – Suarez-Cetrulo, A. L. – Singh, M. – Carbajo, R. S.: AI-driven meat food drying time prediction for resource optimization and production planning in smart manufacturing. IEEE Access, *13*, 2025, pp. 22420–22428. DOI: 10.1109/ACCESS.2025.3534918.
36. Gavai, A. – Bouzembrak, Y. – Mu, W. – Martin, F. – Kaliyaperumal, R. – van Soest, J. – Choudhury, A. – Heringa, J. – Dekker, A. – Marvin, H. J. P.: Applying federated learning to combat food fraud in food supply chains. npj Science of Food, *7*, 2023, article 46. DOI: 10.1038/s41538-023-00220-3.
37. Kamran, R. – Sundarakani, B.: Combining blockchain, IoT and AI for food safety assurance: a systemic approach. In: 2024 IEEE International Conference on Technology Management, Operations and Decisions (ICTMOD). New York : IEEE, 2024, pp. 1–7. ISBN: 979-8-3503-6735-5. DOI: 10.1109/ICTMOD63116.2024.10878247.
38. Williams, M.: Cloud-based machine learning for predicting food spoilage and ensuring safety in the supply chain. Contemporary Journal of Social Science Review, *2*, 2024, pp. 1–26. ISSN: 3006-1466. DOI: 10.12345/agwvrx49.
39. Fattahi, S. H. – Kazemi, A. – Seyfari, Y.: Accurate detection of safflower adulteration in saffron by ATR-FTIR spectroscopy and machine learning algorithms. Journal of Food Measurement and Characterization, *19*, 2025, pp. 6295–6309. DOI: 10.1007/s11694-025-03371-x.
40. Guru, G. P. – Naveen, N. K. – Jain, A. K. – Syed, J. – Baig, R. U.: Convergence of improved

particle swarm optimization based ensemble model and explainable AI for accurate detection of food adulteration in red chilli powder. Journal of Food Composition and Analysis, *143*, 2025, article 107577. DOI: 10.1016/j.jfca.2025.107577.
41. Yin, T. – Peng, Y. – Chao, K. – Qin, J. – Tao, F. – Li, Y. – Ma, Z.: Rapid quantitative detection of Ractopamine using Raman scattering features combined with deep learning. In: Kim, M. S. – Cho, B. (Eds): Proceedings volume 13060. Sensing for Agriculture and Food Quality and Safety XVI. Washington : Society of Photo-Optical Instrumentation Engineers (SPIE), 2024, article 130600D-3. ISBN: 9781510674387. DOI: 10.1117/12.3013271.
42. Prittopaul, P. – Usha, M. – Mary, M. R. – Ram, G. G. – Raj, V. S. A. – Raj, A. G. W.: Texture-based classification of organic and pesticidal spinach using machine learning. In: Suresh, A. – Devi, T. – Deepa, N. – Bashir, A. K. (Eds): Environmental monitoring using artificial intelligence. Beverly : Scrivener Publishing, 2025, pp. 181–200. ISBN: 9781394270361. DOI: 10.1002/9781394270392.ch9.
43. Chen, Y. – Wu, C. – Zhang, Q. – Wu, D.: Review of visual analytics methods for food safety risks. npj Science of Food, *7*, 2023, article 49. DOI: 10.1038/s41538-023-00226-x.
44. Amani, M. A. – Sarkodie, S. A.: Mitigating spread of contamination in meat supply chain management using deep learning. Scientific Reports, *12*, 2022, article 5037. DOI: 10.1038/s41598-022-08993-5.
45. Agarwal, U. – Rishiwal, V. – Shiblee, M. – Yadav, M. – Tanwar, S.: Blockchain-based intelligent tracing of food grain crops from production to delivery. Peer-to-Peer Networking and Applications, *17*, 2024, pp. 3722–3749. DOI: 10.1007/s12083-024-01780-1.
46. Chang, W.-T. – Yeh, Y.-P. – Wu, H.-Y. – Lin, Y.-F. – Dinh, T. S. – Lian, I.-B.: An automated alarm system for food safety using electronic invoices. PLoS One, *15*, 2020, article e0228035. DOI: 10.1371/journal.pone.0228035.
47. Mogilipalem, K. – Poodari, A. K. – Pulipati, Y. – Sangeetha, K. B.: Food spoilage detection using IoT and machine learning. In: 2024 5th International Conference for Emerging Technology (INCET). New York : IEEE, 2024, pp. 1–4. ISBN: 979-8-3503-6115-5. DOI: 10.1109/INCET61516.2024.10593159.
48. Kumar, D. – Bansal, U. – Alroobaea, R. S. – Baqasah, A. M. – Hedabou, M.: An artificial intelligence approach for expurgating edible and non-edible items. Frontiers in Public Health, *9*, 2022, article 825468. DOI: 10.3389/fpubh.2021.825468.
49. Liao, Y. H. – Li, H. H. – Chang, P. C. – Hsu, C. T. – Wang, R. A.: Design an intelligent candy inspection system with AIoT. In: IECC ‘23: Proceedings of the 2023 5th International Electronics Communication Conference (IECC ‘23). New York : Association for Computing Machinery, 2023, pp. 22–26. ISBN: 979-8-4007-0885-5. DOI: 10.1145/3616480.3616484.
50. Kehinde, A. O. – Onafowokan, M. A. – Onalaja, O. O.: Leveraging machine learning for improving food safety standards in Nigeria: a data-driven approach to identifying and mitigating contamination risks. FUDMA Journal of Sciences, *9*, 2025, pp. 130–136. DOI: 10.33003/fjs-2025-0904-3562.
51. Han, J. – Li, T. – He, Y. – Gao, Q.: Using machine learning approaches for food quality detection. Mathematical Problems in Engineering, *2022*, 2022, article 6852022. DOI: 10.1155/2022/6852022.
52. Sun, X. – Liu, F. – Xue, X.: Machine learning combined with electrochemical sensor for rapid detection of Sudan Red I in food. Journal of Food Measurement and Characterization, *18*, 2024, pp. 95–104. DOI: 10.1007/s11694-023-02150-w.
53. Bajaj, A. – Mallick, A. K. – Nath, N. – Akurati, M. – Hussien, M. – Singh, B.: Exploring blockchain’s potential in the global food supply chain through machine learning analysis. In: 2024 International Conference on Artificial Intelligence and Emerging Technology (Global AI Summit). New York : IEEE, 2024, pp. 149–154. ISBN: 979-8-3503-7971-6. DOI: 10.1109/GlobalAISummit62156.2024.10947852.
54. Cui, J. – Wu, C. – Pan, S. – Li, K. – Liu, S. – Lv, Y. – Wang, S. – Luo, R.: Determining the geographical origins of goji berries using a twin-tower multi-feature model. Computers and Electronics in Agriculture, *227*, 2024, article 109571. DOI: 10.1016/j.compag.2024.109571.
55. Çinarer, G. – Doğan, N. – Kılıç, K. – Doğan, C.: Rapid detection of adulteration in pistachio based on deep learning and affordable system design. Multimedia Tools and Applications, *83*, 2024, pp. 14797–14820. DOI: 10.1007/s11042-023-16172-5.
56. Sheriff, I. M. M. – Aravindhar, D. J.: Integrated blockchain-based agri-food traceability and deep learning for profit-optimized supply chain management. In: 2024 Fourth International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT). New York : IEEE, 2024, article 10469024. ISBN: 979-8-3503-4367-0. DOI: 10.1109/ICAECT60202.2024.10469024.
57. Zhang, L. – Yang, Q. – Zhu, Z.: The application of multi-parameter multi-modal technology integrating biosensors and artificial intelligence for rapid detection of food contaminants. Foods, *13*, 2024, article 1936. DOI: 10.3390/foods13121936.
58. Floridi, L. – Cowls, J. – Beltrametti, M. – Chatila, R. – Chazerand, P. – Dignum, V. – Luetge, C. – Madelin, R. – Pagallo, U. – Rossi, F. – Schafer, B. – Valcke, P. – Vayena, E.: AI4People – An ethical framework for a good AI society: opportunities, risks, principles, and recommendations. Minds and Machines, *28*, 2018, pp. 689–707. DOI: 10.1007/s11023-018-9482-5.
59. Gunning, D. – Aha, D. W.: DARPA’s Explainable Artificial Intelligence (XAI) Program. AI Magazine, *40*, 2019, pp. 44–58. DOI: 10.1609/aimag.v40i2.2850.
60. Smuha, N. A.: Beyond the individual: governing AI’s societal harm. Internet Policy Review, *10*, 2021, article 1574. DOI: 10.14763/2021.3.1574.

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